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Residential demand response in the European power system: No significant impact on capacity expansion and cost savings

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ABSTRACT

Direct Load Control (DLC) is a demand response strategy in which customers receive compensation from utilities in return for permitting them to regulate the operation of specific equipment. This paper analyzes the impacts of DLC programs on the transition to renewable energy within the European electricity system towards 2060. The study quantifies the achievable hourly potential for DLC across Europe in the residential sector. By implementing and developing a DLC module within the stochastic capacity expansion model EMPIRE, we investigate how costs, long-term investments, and long-term marginal prices are affected by residential DLC participation rates. The research utilizes a comprehensive DLC dataset, including ten appliances such as electric vehicles, heat pumps, refrigeration, and others. This dataset serves as the basis for creating four storylines to investigate the integration of these programs into the European electricity system. The results indicate that residential DLC programs have some impact on grid-battery deployment, PV plant penetration, and electricity prices. In the best-case scenario, involving ambitious participation of residential loads in DLC programs without compensation, cost savings are about 1% versus not introducing DLC. The findings contribute to understanding the value of demand response programs in Europe, indicating that the savings they bring might not be sufficient to provide enough incentives or compensation for widespread participation in such programs. That is, from a long-term investment or capacity expansion perspective, it may not be worthwhile to soley include residential demand response in the planning of the electricity system.

1. Introduction

The European electricity system is undergoing a transformation with the rapid integration of Variable Renewable Energy Sources (VRES) driven by rising electricity demand, cost competitiveness, and climate policies [1]. This evolution necessitates greater system flexibility due to the growth of VRES and the phasing out of conventional thermal power plants [2]. A potential focus is now on demand-side management [3,4] to shape electricity demand, influencing both long-term capacity investments and short-term price variability [5]. In this regard, the deployment of smart meters in Europe has enabled a bottom-up restructuring of the electricity sector. With over half of EU countries reaching a minimum of 10% smart meter penetration and ten countries exceeding 80% [6], end-users are no longer passive consumers with fixed electricity demands. Emphasizing the importance of end-users, the EU Strategic Energy Technology Plan [7] places them at the heart of the European energy transition, recognizing their potential to generate, store, and manage electricity. Hence, the development prospects of demand response programs offer possibilities for empowering consumers and shaping the investments for a low-carbon power system.

In the literature, demand response impacts on the capacity expansion of the power system has been explored in some computational studies. De Jonghe et al. [8] develop three deterministic mathematical programming methods to study the impact of demand response on the cost-optimal generation mix, and they find that demand response facilitates increased investments in wind capacity. Asensio et al. [9] develop a bi-level optimization model considering capacity expansion

Abbreviations: SOC, State of Charge; DLC, Direct Load Control; DR, Demand Response; RLG, Responsive Load Group; ESS, Energy Storage System; VRES, Variable Renewable Energy Sources; DW, Dishwasher; WM, Washing Machine; TD, Tumble Dryer; SH, Space Heater; HP, Heat Pump; WH, Water Heater; CP, Circulation Pump; AC, Air Conditioning; Ref, Refrigerators and freezers; EV, Electric Vehicle; EMPIRE, European Model for Power system Investments with Renewable Energy; NUTS, Nomenclature of territorial units for statistics

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and demand response, and they demonstrate that demand response can defer network investments by solving an equivalent deterministic mixed-integer linear program. Misconel et al. [10] use a deterministic linear program (ELTRAMOD) to compare demand response impacts in two 100% renewable electricity systems: one centralized relying on wind power and one decentralized relying on solar power. This and other related studies assume demand response estimates, see review in [11]. A central work on estimating theoretical estimates of European demand response has been the work of [12,13] while authors in [11] propose a methodology to calculate estimates of demand response for different categories. In contrast, [14] performs an empirical study for the U.S. based on actual experiences of industrial loads and their value for peak load reduction. Other studies combine estimates with empirical findings in the context of micro-grids [15,16].

Whether empirical or theoretical in nature, a central question remains: does the value of demand response outweigh its costs, i.e., does it provide enough incentive for participation? For instance, [17] estimates the total demand response potential in Northern Europe to be between 15% to 30% of peak demand. They find that demand response yields lower costs and emissions. Similarly, [18] notes the role of demand response in reducing prices in capacity markets. Despite these potentials, technical and social barriers to demand response deployment are reviewed by [19], while [20] conducts cost–benefit analyses to review the economic viability of demand response. Both studies note the uncertainty of demand response measurement and verification as well as the lack of energy market setting (e.g., well-established marketplaces for demand-side flexibility).

Other studies have shown the importance of considering endogenous uncertainty when assessing the capacity expansion of the power system with large penetration of VRES [21–23]. Although most studies exploring demand response do not consider endogenous uncertainty [8–10], this is partially addressed by [24], who explore the impact of seven groups of demand response in the residential, industrial, and commercial sectors on the European power system towards 2050. There, demand response potentials are assumed to respond perfectly to market signals by performing a system wide cost minimization, i.e., demand response is simulated as Direct Load Control (DLC). However, the authors estimate direct load control potentials based on theoretical estimates from a study in Germany [25]. To ensure a more realistic estimation of demand response potential in capacity expansion models, equivalent direct load control potential must consider the residential sector's willingness for DLC and the technical load shift constraints, including response time, shift time, and hourly availability. That is, existing literature has used mostly theoretical estimates of demand elasticity and uniformly applied to the residential sector (e.g., not distinguishing appliances or EVs) and without distinctions between European countries (e.g., willingness to load shifting in Spain is different than in Norway).

In this paper, we present a novel DLC module integrated into a capacity expansion model (EMPIRE model[1]), offering fresh insights into the willingness of residential consumers in Europe to engage in demand response programs. By employing an empirical study applied to real life consumers, we assess achievable residential flexibility using an extensive dataset encompassing demand response participation in all of Europe, while also including the actual willingness to participate in DLC programs. The computational study explores various scenarios for residential DLC program participation factors up to 2060. To the authors' knowledge, no previous study has explored DLC impacts on long-term capacity expansion of the European electricity system towards 2060 considering endogenous uncertainty while using real empirical estimates of the hourly DLC potential from the residential sector encompassing multiple appliances and all European countries. In short, the paper's main contributions are as follows:

- Quantify the achievable hourly potential of residential DLC across Europe from 2023 to 2060 using the stochastic capacity expansion model EMPIRE. This constitutes a large-scale computational analysis conducted in 31 European countries, covering multiple investment periods (2023 to 2060) while ensuring the representation of hourly supply–demand balance.
- Develop a new DLC module for the EMPIRE model. Also, release the updated version of the open source EMPIRE modeling framework with the DLC module[2]
- Quantify how costs, investments, and long-term marginal prices in the European electricity system are impacted by different participation rates for residential DLC across Europe.
- Provide a wide range of sensitivity analyses to illustrate the low value DLC provides compared to the incentives required to activate demand response.

The remainder of the paper is organized into four sections: Section 2 describes the input data and DLC constraints as well as the simulation instances (case studies). Section 3 describes the EMPIRE model and the DLC module developed in the computational study. Section 4 presents the results, and Section 5 suggests further work and concludes this paper.

2. Computational study and input data

This section briefly covers the DLC dataset and flexibility constraints employed in this study before delving into the mathematical formulation of the DLC module within the EMPIRE modeling framework, along with necessary adjustments for its implementation.

2.1. Raw direct load control dataset

The ten residential devices used in this study were selected due to their high-power demand and ability to be flexible with regard to timing of use. The electric consuming devices are Dishwasher (DW), Washing Machine (WM), Tumble Dryer (TD), electric Space Heater (SH), electric air-to-air Heat Pump (HP), electric Water Heater (WH) with storage capabilities, heat Circulation Pump (CP), Air Conditioning (AC), Refrigerators and freezers (Ref), and fully battery Electric Vehicle (EV). Annual demand profiles for each of these devices are generated on the NUTS2 (Nomenclature of territorial units for statistics (NUTS)) level for the EU27, United Kingdom, Switzerland, and Norway on an hourly granularity from 2022 to 2050 for a representative day for each month (i.e. 24 h for an average day in each month). A combination of R [27] and Python [28] were used for data processing, estimation of demand flexibility, and visualization. The Python and R scripts along with the input and final data for this paper are freely available for external users. These resources are hosted on Zenodo (see O'Reilly et al. [29]).

2.2. Direct load control participation

As previously mentioned, existing literature has explored Pan-European analyses and the attainable potentials of residential demand response, although these estimations have certain limitations [11,25]. With these considerations in mind, our study derives realistic participation rates for DLC programs by conducting a comprehensive literature review, as summarized in the Appendix (Table 5). To account for optimism bias, participation rates obtained from surveys were adjusted by a factor of 0.45 before calculating the *Average DR Participation - Adjusted*, indicated in the final row for each device.[3] This conservative adjustment factor, derived from AEG [31], was determined by

[1] European Model for Power system Investments with Renewable Energy (EMPIRE) developed at NTNU, refer to more details and information at Backe et al. [26] and https://www.ntnu.edu/web/iot/energy/energy-models-hub/empire.

[2] Refer to version 1.1.0 of EMPIRE (Access link).

[3] For further insight into optimism bias, refer to Flyvbjerg [30].

Table 1
DLC participation by country and device (N = 6163).

Countries	Wash	Ref	Air conditioning	Water heater	Heat	Electric vehicle	Other
Austria	23.1	25	16	22.2	15	19.7	13.4
Belgium	11.9	12.8	8.2	11.4	7.7	10.1	6.9
Bulgaria	35.4	38.3	24.6	34	23	30.1	20.6
Croatia	34.4	37.1	23.8	33	22.3	29.2	20
Cyprus	14.1	15.3	9.8	13.6	9.2	12	8.2
Czech_Republic	19.7	21.3	13.7	18.9	12.8	16.8	11.5
Denmark	18	19.4	12.5	17.3	11.6	15.3	10.4
Estonia	22.1	23.9	15.3	21.3	14.3	18.8	12.9
Finland	22.8	24.6	15.8	21.8	14.7	19.3	13.2
France	31.5	34	21.8	30.2	20.4	26.7	18.3
Germany	16.2	17.5	11.2	15.6	10.5	13.8	9.4
Greece	31.8	34.3	22	30.5	20.6	27	18.5
Hungary	33.1	35.7	22.9	31.7	21.4	28.1	19.2
Ireland	28.4	30.7	19.7	27.2	18.4	24.1	16.5
Italy	28	30.2	19.4	26.8	18.1	23.8	16.2
Latvia	21.2	22.9	14.7	20.4	13.7	18	12.3
Lithuania	30.4	32.8	21	29.1	19.7	25.8	17.6
Luxembourg	15.8	17.1	11	15.2	10.2	13.4	9.2
Malta	29.9	32.2	20.7	28.6	19.3	25.4	17.3
Norway	18.6	20.1	12.9	17.8	12	15.8	10.8
Poland	24.5	26.5	17	23.5	15.9	20.8	14.2
Portugal	43.3	46.8	30	41.6	28	36.8	25.2
Romania	35.3	38.1	24.5	33.9	22.9	30	20.5
Slovakia	31.1	33.6	21.5	29.8	20.1	26.4	18.1
Slovenia	30.2	32.6	20.9	28.9	19.5	25.6	17.5
Spain	26.6	28.7	18.4	25.5	17.2	22.6	15.4
Sweden	23.3	25.2	16.2	22.4	15.1	19.8	13.6
Switzerland	39.2	42.3	27.1	37.6	25.4	33.3	22.8
The Netherlands	15.2	16.4	10.5	14.6	9.9	12.9	8.8
United Kingdom	21.7	23.4	15	20.8	14	18.4	12.6
Average	26.35	28.46	18.25	25.28	17.06	22.38	15.3

Notes: Wash: includes washing machines, tumble driers, and dish washers; Ref: includes refrigerators and freezers; and Heat: includes electric storage heater, heat pumps, and heat circulation pumps.

comparing unadjusted adoption rates of a specific program to actual program participation rates across diverse jurisdictions in the Midwest USA.

Due to the heterogeneity between the countries in our study, the 2018 Pan-European survey from the ECHOES H2020 project [32] was re-analyzed and applied to the results of the literature review to capture country-level differences in the willingness to participate in DLC. This question is reproduced below.

> *Would you allow your grid operator to remotely switch on and off non critical appliances in your home if you were offered an annual discount of [Bid value]?*

The responses were based on a five point likeability scale from 'very unlikely' to 'very likely'. A respondent was coded as 1 if they responded 'likely' or 'very likely' and a 0 otherwise. The 'bid value' was country specific and given in the respondent's national currency. These bid values were calculated to be 10% of the average annual household electricity expenditure in each nation. Thus, these bid values are weighted by the relative cost of electricity in each nation. The result for each country was divided by the average of the sample (35%) and multiplied by the *Average DR Participation - Adjusted* to estimate the participation rates for the device in each country that are shown in Table 1. The profiles described in Section 2.1 are multiplied with the participation rates shown in this section to attain achievable–technical–economic potentials.

2.3. Quantitative characterization of flexible residential loads

The flexibility of the devices are constrained by power and operational limitations. *Max Capacity* is the upper limit for power demand with respect to the device type, region, and year. It is estimated using the number of residential devices and the nominal power of the device type. *Max Reduction* is the load for each device which is estimated using the hour's share of the annual final energy demand. *Max Dispatch* is the difference between *Max Capacity* and *Max Reduction*. It represents the potential for increasing power demand in a given hour. Scaling the power constraints by the participation rates adjusts them from theoretical potentials to realistic potentials by considering the likelihood of residential participation.

Table 2 below, shows the operational limitations that identify whether the load can be delayed, advanced, or both (*DLC direction*) and how many hours the DLC event can take place (*t.shift*). Our study estimates the contribution of pan-European residential direct load control (DLC) to support the transition to a carbon free energy system using Gils [12] as a starting point for residential flexibility. Capturing region specific DLC strategies is out of scope of the project but we believe the parameter selection and residential focus provides enough evidence to achieve the study objective and detail to support future region specific investigation. In a real-world application, various control strategies can be employed to optimize the operation of heating, ventilation, and air conditioning (HVAC) systems. The t.shift parameter, or duration of a DLC event, is defined as the length of time a residential device can be delayed or advanced before the load needs to be balanced. Viable t.shift parameters and DLC program characteristics (e.g., DLC event duration and frequency) depend on local climate, thermal insulation, comfort levels, level of activity in the household, and remuneration for the participation. Hence, for some countries or regions our parameters may be unrealistic and thus a word of caution is given when applying them to a broader context.

Average hourly flexibility potentials by country and selected years are shown in Fig. 1.[4] The values in Fig. 1 are the yearly average of the aggregated hourly potentials for load delay and load advancement. Differences in country populations captures most of the variation seen

[4] These values have not been adjusted by country level participation rates — theoretical-technical-economic potentials.

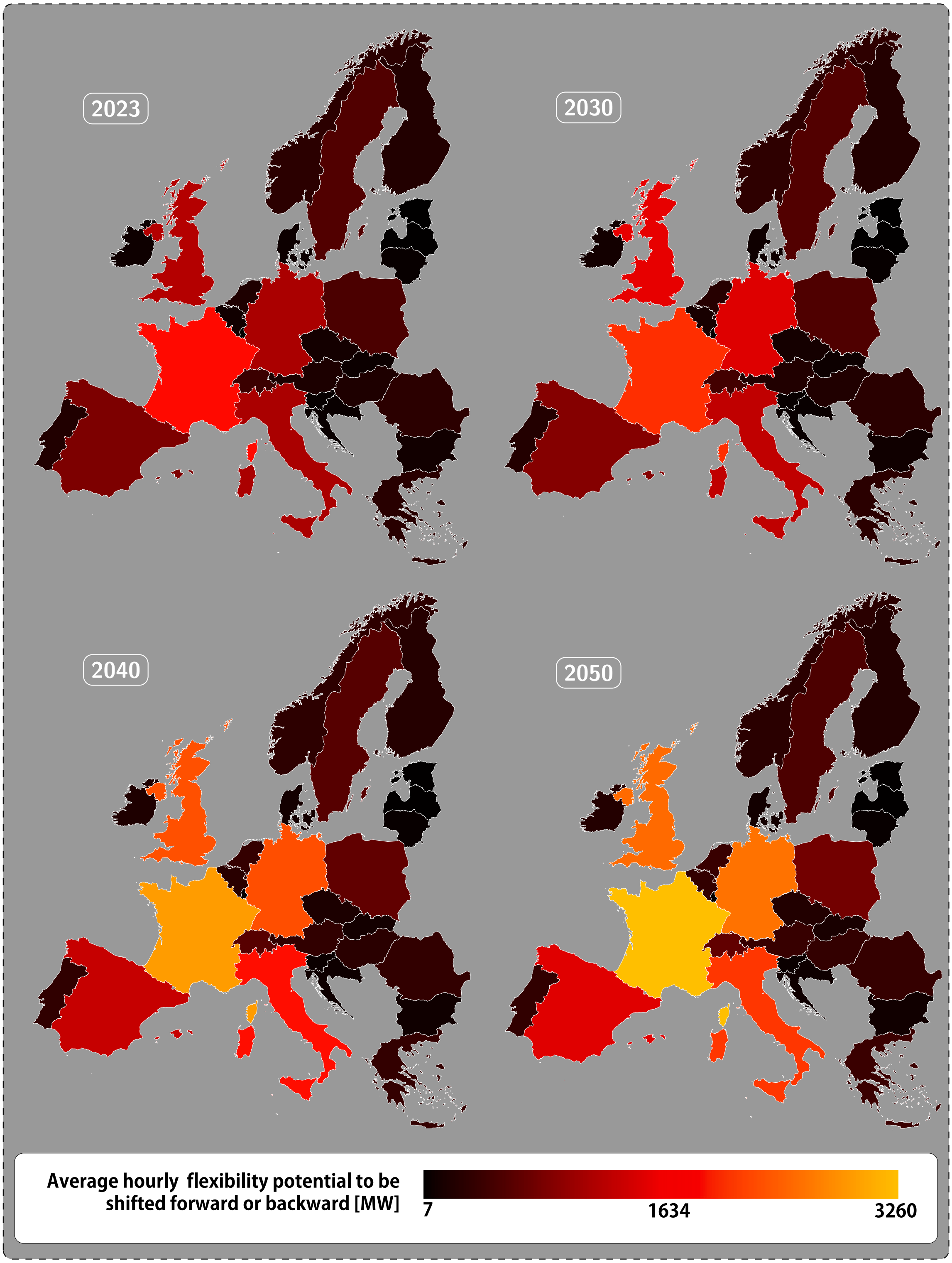

Fig. 1. Average hourly flexibility potentials for sample countries and select years (MW).

between countries for a particular year. The growth in flexibility potentials across time is largely driven by the expectations for high electric vehicle and heat pump saturation. France shows the highest potential for load delay and advancement for all the years with 1714 MW, 2028 MW, 2963 MW, and 3260 MW for 2023, 2030, 2040, and 2050, respectively. Luxembourg shows the highest growth rate in flexibility potential for the sample between the select years. The increase from 15 MW of potential to 28 MW between 2030 and 2040 is due to the high annual replacement rate of their vehicle stock (12%) and expectations in their electric vehicle transition for the country [37–39]. For more information and details on the DLC dataset refer to [40].

2.4. Adjusting direct load control dataset to be used in EMPIRE

The following adjustments are made in the raw DLC dataset to align it with EMPIRE:

Table 2
Demand response shift constraints.

Appliance	DLC direction	t.shift	Reference
Electric Vehicle	Delay	4	[33][a]
Dryer	Delay and Advance	6	[12]
Washing Machine	Delay and Advance	6	[12]
Dish Washer	Delay and Advance	6	[12]
Storage Heater	Advance	12	[12]
Water Heater	Advance	12	[12]
Refrigeration	Delay	2	[12]
Air Conditioning	Delay	2	[12]
Circulation Pump	Delay	2	[12]
Heat Pump	Advance	2	[34–36][a]

[a] Conservative values were assumed based on the literature.

1. The DLC dataset provides estimates on the NUTS2 level DLC potentials. However, in EMPIRE each country is considered as a single node to diminish the computational burden of the problem. In this regard, the DLC potential of all NUTS2 level nodes of each county is aggregated in the first step. There is only one exception. Unlike all other countries, Norway is modeled as five nodes. The NUTS2 level regions of Norway are then mapped into these five nodes as follows: NO02 → NO1; NO08 → NO1; NO09 → NO2; NO06 → NO3; NO07 → NO4; and NO0 A → NO5.
2. The DLC dataset provides estimates from 2020–2050. The horizon of our study is from 2020 to 2060. We have assumed that the DLC potentials remain constant from 2050 to 2060. However, in the storylines that are defined later in this study, an increase factor is considered which results in higher DLC potential year by year.
3. As mentioned in Section 2, there are ten appliances in the provided DLC data set. The goal of this study is not to assess the impact of each appliance separately. Therefore, we aggregate the loads based on their responsiveness — similar shift times and direction of load shifts (i.e., delay and advance). This classification decreases the computational burden of the model. In this study, the loads are categorized into the following five Responsive Load Groups (RLGs):

    - **RLG1:** Air conditioning, refrigeration, and circulation pumps (only can be delayed up to two hours)
    - **RLG2:** Dryer, washing machine, and dishwasher (can be both delayed and advanced up to six hours)
    - **RLG3:** Storage heater and water heater (only can be advanced up to 12 h)
    - **RLG4:** Electric vehicle (only can be delayed up to four hours)
    - **RLG5:** Heat pump (only can be advanced up to two hours)

2.5. Participation of residential loads in DLC programs: Storylines

To comprehensively discuss the impact of responsive loads on the energy transition in the European power system, four storylines were implemented:

- **Base Case:** No DLC program considered.
- **Case I:** For this case, we utilized the DLC dataset explained in Section 2.1. Accordingly, we assumed that the participation rates of loads – a metric that indicates the willingness of loads to participate in DLC programs – remain constant for all years. The maximum reductions and increases of each year are then calculated by multiplying the theoretic flexibility potentials of that year and the fixed participation rates of related countries and load types. However, the assumption that the participation rates remain constant may not be entirely realistic. To this end, we also introduced Case **II**.
- **Case II:** In this scenario, we assume that an increasing number of loads become interested in participating in DLC programs. Specifically, we assume that 4% of new loads – those that were not previously participating in DLC programs – decide to enroll each year. Fig. 2 shows the average participation rates of various appliances in several sample years for this case.
- **Case III:** In this case, we assume that all the residential loads are willing to participate in DLC programs. This case may not be realistic; however, through it, we can investigate the maximum realistic impact of participation of residential loads on the transition of the European electricity system.
- **Case IV:** This case is the same as **Case II** with double shift times. There is a limitation with the DLC module in the EMPIRE modeling framework; the shift times are modeled through sequential time windows with the duration of shift times. Concerning this explanation, the loads cannot be shifted between these windows. Therefore, the results yield a lower bound of the impact of DLC programs, and increasing the shift times will compensate for this.

3. Method

3.1. Overview of the EMPIRE modeling framework

EMPIRE is a linear multi-horizon stochastic programming model to study long-term investment planning of a power system. The electricity system is presented as a network of nodes and arcs in the model. The nodes represent a country or a region, whereas the arcs represent cross-border transmission between countries/regions. The model takes decision on two temporal scales: (i) an *investment* temporal scale with 5-year time steps, and (ii) an *operational* temporal scale with hourly time steps. The input to the model includes technology costs, existing capacities, technological constraints, maximum resource potential, carbon emission constraints, and demand, while the output includes investments and production in generation, storage, and transmission, as well as resulting carbon emissions. The model has been used in multiple studies to analyze the decarbonization of the European power system. The EMPIRE model was recently published as an open-source model [26].

Investment decisions in EMPIRE are first-stage decisions in the model, meaning investment decisions are made subject to endogenous operational uncertainty through the representation of different stochastic operational scenarios. Note that we do not consider uncertainty regarding long-term assumptions, e.g., future technology costs or long-term electricity demand development.

Operational decisions are second-stage decisions, meaning they are made with perfect information within each operational scenario. The difference between operational scenarios represents the short-term uncertainties related to the variable production of renewable energy resources and system load. The operational scenarios are either representative seasonal weeks (168 h) or representative peak days (24 h). For each investment period, there are at least four representative weeks (winter, spring, summer, and fall) and two representative peak days. One of the peak days contains the highest load combined for all countries/regions, and the other peak day contains the highest load of any single country/region.

The objective of EMPIRE is to optimize the long-term investments in generation, storage, and cross-border transmission subject to optimized operations within each stochastic scenario. Assuming that the electricity market is perfectly competitive, the objective is to minimize the system's total cost:

$$\min z = \sum_{i\in\mathcal{I}} (1+r)^{-5(i-1)} \times \Big[\sum_{n\in\mathcal{N}} \sum_{g\in\mathcal{G}_n} c^{\text{gen}}_{g,i} x^{\text{gen}}_{n,g,i} + \sum_{l\in\mathcal{L}} c^{\text{tran}}_{l,i} x^{\text{tran}}_{l,i} +$$

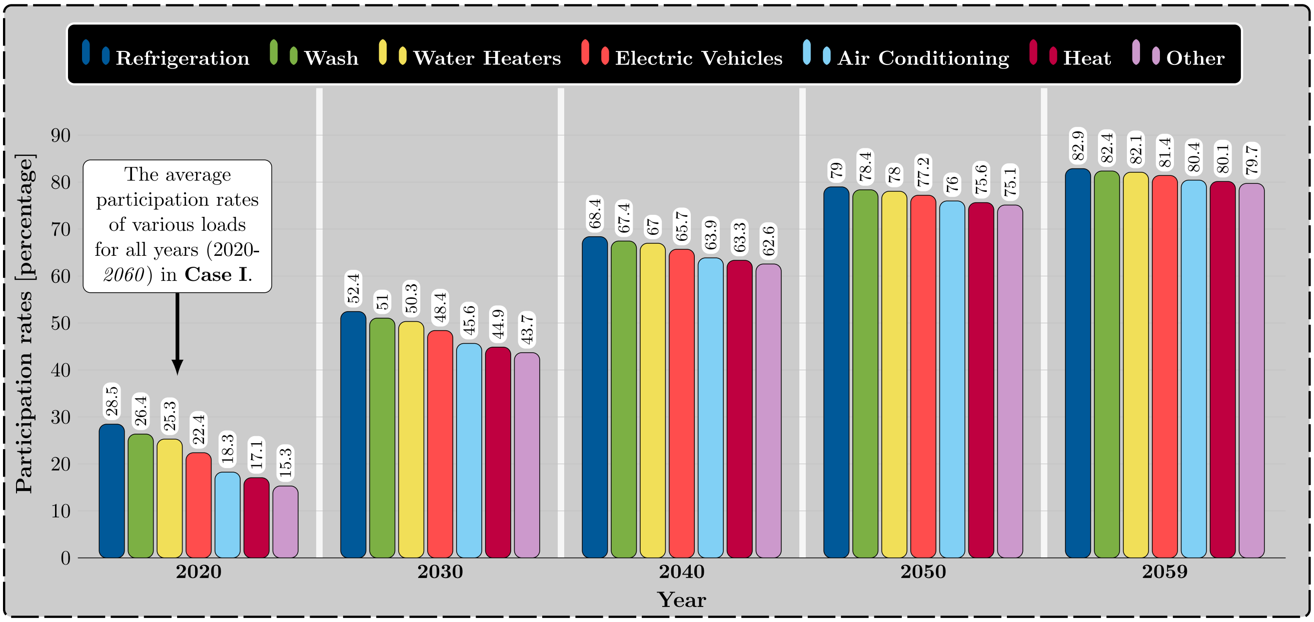

Fig. 2. Average participation rates of various residential loads for some sample years in Case **II** and Case **IV** .

$$\sum_{n\in\mathcal{N}}\sum_{b\in\mathcal{B}_n}\left(c^{\mathrm{storPW}}_{b,i}x^{\mathrm{storPW}}_{n,b,i}+c^{\mathrm{storEN}}_{b,i}x^{\mathrm{storEN}}_{n,b,i}\right)+$$

$$\vartheta\sum_{\omega\in\Omega}\pi_\omega\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\sum_{n\in\mathcal{N}}\left(\sum_{g\in\mathcal{G}_n}q^{\mathrm{gen}}_{g,i}y^{\mathrm{gen}}_{n,g,h,i,\omega}+q^{\mathrm{ll}}_{n,i}y^{\mathrm{ll}}_{n,h,i,\omega}\right)\Bigg]. \quad (1)$$

The first four terms in Eq. (1) quantifies the capital expenditure for investments in generator types $\mathcal{G}$, transmission lines, and storage types $\mathcal{B}$ summed over all nodes $\mathcal{N}$ and bidirectional arcs $\mathcal{L}$. The last two terms in (1) quantifies expected operational expenditure for generator types $\mathcal{G}$ and load shedding scaled with the scenario probability π and the seasonal weighting factor α to scale representative time periods to one year. Note that all costs are discounted at an annual rate r, and operational expenditure is scaled with $\vartheta=\sum_{j=0}^{4}(1+r)^{-j}$ to represent a five year period.

For more details on the mathematical formulation of EMPIRE, please see the software documentation provided in the open source repository [26].

3.2. Direct load control module in EMPIRE

The EMPIRE modeling framework has been equipped with a DLC module, enabling us to incorporate DLC programs in the long-term investment planning of an electricity system. Each responsive load group (RLG) within the DLC module is represented as a *virtual* Energy Storage System (ESS), with charging/discharging efficiency of one. Accordingly, the mathematical formulation of the constraints that describe RLGs and ESSs are almost the same. In this regard, the notation of the variables associated with RLGs is similar to those of ESSs, but may convey different meanings. For example, y^{chrg} and y^{dischrg} denote respectively the upward and downward deviations from the base load profile for RLGs, which is different from charging and discharging of ESS. Note that Table 3 presents an overview of the notation of the variables and parameters for the DLC module in EMPIRE.

Two types of costs are associated with DLC programs: (1) cost of payments to responsive loads for DLC activation and (2) technological costs, including equipment, software, and human resources. The activation cost associated with DLC programs is integrated into the model by incorporating the following term into the objective function:

$$\vartheta\sum_{\omega\in\Omega}\pi_\omega\sum_{s\in\mathcal{S}}\alpha_s\sum_{n\in\mathcal{N}}\sum_{b\in\mathcal{B}^{\mathrm{DR}}_n}q^{\mathrm{DLCpay}}_{n,b,i}\sum_{h\in\mathcal{H}_s}\frac{y^{\mathrm{dischrg}}_{n,b,h,i,\omega}+y^{\mathrm{chrg}}_{n,b,h,i,\omega}}{2}, \quad (2)$$

Table 3
Notation and symbols.

Indices and Sets	
$\mathcal{B}_n(b)$	Set (index) of ESSs (including RLGs) at node n.
$\mathcal{B}^{\mathrm{DR}}_n\subset\mathcal{B}_n$	Set of RLGs at node n.
$\underline{\mathcal{B}}^{\mathrm{DR}}_n\subset\mathcal{B}^{\mathrm{DR}}_n$	Set of delaying-only RLGs at node n.
$\overline{\mathcal{B}}^{\mathrm{DR}}_n\subset\mathcal{B}^{\mathrm{DR}}_n$	Set of advancing-only RLGs at node n.
$\mathcal{H}_s=\{h^1_s,h^2_s,\ldots,\lvert\mathcal{H}_s\rvert\}$	Set (index) of operational periods within season s.
$\mathcal{I}(i)$	Set (index) of investment periods.
$\mathcal{N}(n)$	Set (index) of nodes.
$\mathcal{S}(s)$	Set (index) of seasons.
$\Omega(\omega)$	Set (index) of scenarios.
Parameters	
$q^{\mathrm{DLCpay}}_{n,b,i}$	DLC activation cost of RLG b.
$DR^{\mathrm{maxDis}}_{n,b,h,i,\omega}$	Maximum potential of hourly upward deviation from the base load profile (load increase) for RLG b at node n, investment period i, hour h, and scenario ω.
$DR^{\mathrm{maxRed}}_{n,b,h,i,\omega}$	Maximum potential of hourly downward deviation from the base load profile (load decrease) for RLG b at node n, investment period i, hour h, and scenario ω.
$DR^{\mathrm{bline}}_{n,b,h,i,\omega}$	Cumulative value of the parameter $DR^{\mathrm{maxRed}}_{n,b,h,i,\omega}$ over operational hours (h) for RLG b at node n, investment period i, hour h, and scenario ω.
$DR^{\mathrm{max}}_{n,b,h,i,\omega}$	Maximum upward deviation of RLG b from its cumulative base load profile. A parameter defined to model shift windows.
$DR^{\mathrm{min}}_{n,b,h,i,\omega}$	Maximum downward deviation of RLG b from its cumulative base load profile. A parameter defined to model shift windows.
t^{shift}_b	Shif time or the maximum number of hours the DLC event can take place (also referred to as *t.shift*).
Operation-related variables	
$w^{\mathrm{StorOpe}}_{n,b,h,i,\omega}$	If $b\in B^{\mathrm{DR}}$: Net deviation from the cumulative base load profile ($DR^{\mathrm{bline}}_{n,b,h,i,\omega}$) of RLG b until operational hour h at node n, investment period i, and scenario ω.
$\eta^{\mathrm{chrg}}_{i,b}$	Loss percentage when increasing or decreasing load. If $b\in B^{\mathrm{DR}}$ this parameter is equal to one.
$y^{\mathrm{chrg}}_{n,b,h,i,\omega}$	If $b\in B^{\mathrm{DR}}$: Hourly upward DLC activation (load increase) for RLG b at node n, investment period i, hour h, and scenario ω.
$y^{\mathrm{dischrg}}_{n,b,h,i,\omega}$	If $b\in B^{\mathrm{DR}}$: Hourly downward DLC activation (load reduction) for RLG b at node n, investment period i, hour h, and scenario ω.

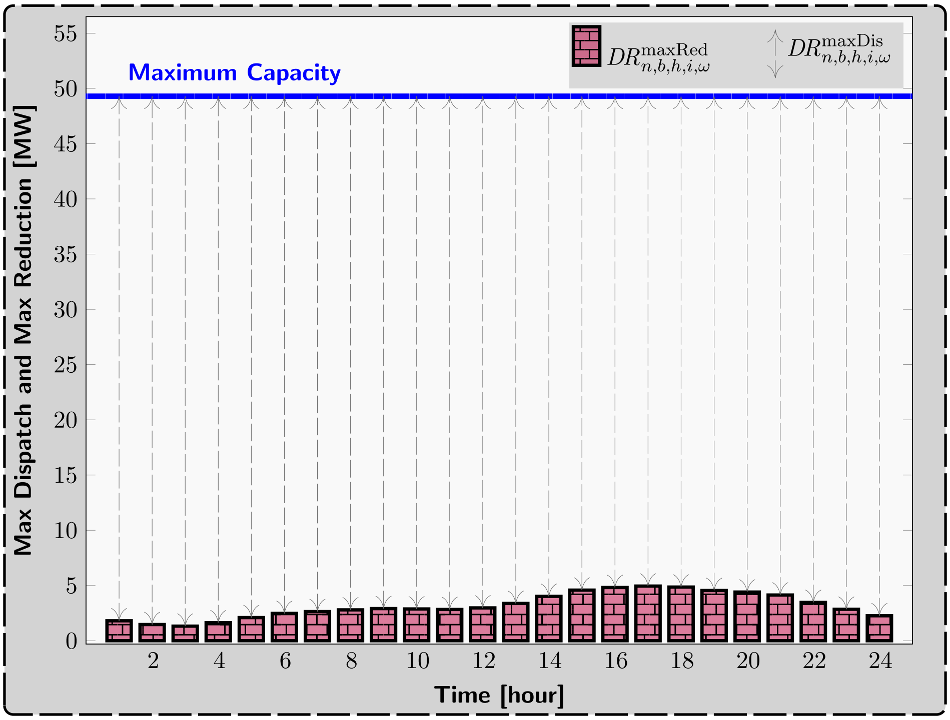

Fig. 3. Illustration of DLC module main parameters ($DR^{\mathrm{maxRed}}_{n,b,h,i,\omega}$, $DR^{\mathrm{maxDis}}_{n,b,h,i,\omega}$) for a sample scenario of RLG4 in Austria during investment period 2020–2025.

where $q^{\mathrm{DLCpay}}_{n,b,i}$ represents DLC activation cost, which is multiplied by the total activated DLC. The total activated DLC is half of the accumulated values of $y^{\mathrm{dischrg}}_{n,b,h,i,\omega}$ and $y^{\mathrm{chrg}}_{n,b,h,i,\omega}$ because the other half represents the recovery of the activated DLC. All the other parameters in this expression have been explained below Eq. (1). The payment cost is disregarded in the first set of case studies, referred to as **(P0)**. Consequently, the results reveal the maximum benefit of implementing residential DLC programs. However, when no DLC activation cost is considered, the responsive loads may be activated without impacting the objective function. To phase out the non-beneficial DLC activation, a set of case studies with a small activation cost for DLC, referred to as **(P1)**, is also investigated. The results provide valuable information, including the average present value of DLC activation per MWh, aiding stakeholders and policymakers in assessing the financial benefits and feasibility of adopting such programs. Additionally, for further analysis, a separate section (Section 4.6) is designated to study the impact of operational costs associated with the implementation of DLC programs.

Technological costs associated with DLC programs can be implemented similarly to the ESS's investment costs existing in EMPIRE; however, in this study, these costs are overlooked due to the limited available data. This assumption is justifiable since homeowners themselves bear a significant portion of the technological expenses related to DLC programs, particularly the technologies involved in transitioning to smart homes in residential sectors. Moreover, it is noteworthy that the information and communication technologies required for implementing DLC programs are also utilized for other purposes, such as meter reading in residential sectors, thereby reducing the manpower required for this task.

3.2.1. Parameters of the DLC module in EMPIRE

To begin with, it is important to note that the current version of the DLC module within EMPIRE necessitates the pre-calculation of a few parameters. These parameters are derived from two available parameters in the raw DLC dataset: *maximum reduction* and *maximum dispatch*, denoted with $DR^{\mathrm{maxRed}}_{n,b,h,i,\omega}$ and $DR^{\mathrm{maxDis}}_{n,b,h,i,\omega}$, respectively. The key parameters that require pre-calculation are denoted as $DR^{\mathrm{bline}}_{n,b,h,i,\omega}$, $DR^{\mathrm{min}}_{n,b,h,i,\omega}$, and $DR^{\mathrm{max}}_{n,b,h,i,\omega}$ (refer to Table 3). This section provides an illustrative example of how these parameters are calculated. Note that in this example, the duration of the regular season – a parameter of EMPIRE – is assumed to be 24 h.

Fig. 3 illustrates the two available parameters in the raw DLC dataset – namely *maximum reduction* ($DR^{\mathrm{maxRed}}_{n,b,h,i,\omega}$) and *maximum dispatch* ($DR^{\mathrm{maxDis}}_{n,b,h,i,\omega}$) – for RLG4, which only includes electric vehicles, for a specific node and investment period spanning over 24 h. As depicted in this figure, the sum of these two parameters remains constant and is equivalent to the load demand of a case in which all loads within the RLG are simultaneously connected to the grid, referred to as *Maximum capacity*. *Maximum reduction* represents the base load profile of RLG4, that is, the portion of RLG4's load demand connected to the grid at hour h. *Maximum dispatch* is then the difference between these two parameters.

Moving on the next parameter, $DR^{\mathrm{bline}}_{n,b,h,i,\omega}$, it represents the cumulative values of $DR^{\mathrm{maxRed}}_{n,b,h,i,\omega}$ over the window of a regular season. Mathematically, it is calculated as follows:

$$DR^{\mathrm{bline}}_{n,b,h,i,\omega} = \sum_{h'=h^1_s}^{h'\leq h} DR^{\mathrm{maxRed}}_{n,b,h',i,\omega} :$$

$$\forall_n \in \mathcal{N},\ \forall_b \in \mathcal{B}^{\mathrm{DR}},\ \forall_h \in \mathcal{H}_s,\ \forall_s \in \mathcal{S},\ \forall_i \in \mathcal{I}, \forall_\omega \in \Omega. \tag{3}$$

The two remaining parameters, $DR^{\mathrm{min}}_{n,b,h,i,\omega}$ and $DR^{\mathrm{max}}_{n,b,h,i,\omega}$, are specifically defined to model the shift windows. Fig. 4 visually presents these two parameters along with $DR^{\mathrm{bline}}_{n,b,h,i,\omega}$ for the same node and investment period as illustrated in Fig. 3. Within each shift window, the values of DR^{max} are equal to the value of DR^{bline} at the end of the shift window, and the values of DR^{min} are equal to the value of DR^{bline} at the hour before the beginning of the shift window. Mathematically, these are expressed as follows:

$$DR^{\mathrm{min}}_{n,b,h,i,\omega} = DR^{\mathrm{bline}}_{n,b,h',i,\omega} : \tag{4}$$

$$\forall_n \in \mathcal{N},\ \forall_b \in \mathcal{B}^{\mathrm{DR}},\ \forall_h \in \mathcal{H}_s, \forall_s \in \mathcal{S},\ \forall_i \in \mathcal{I}, \forall_\omega \in \Omega, h' = \left\lfloor \frac{h}{t^{\mathrm{shift}}_b+1} \right\rfloor \times (t^{\mathrm{shift}}_b+1),$$

$$DR^{\mathrm{max}}_{n,b,h,i,\omega} = DR^{\mathrm{bline}}_{n,b,h',i,\omega} : \tag{5}$$

$$\forall_n \in \mathcal{N},\ \forall_b \in \mathcal{B}^{\mathrm{DR}},\ \forall_h \in \mathcal{H}_s, \forall_s \in \mathcal{S},\ \forall_i \in \mathcal{I}, \forall_\omega \in \Omega, h' = \left\lceil \frac{h}{t^{\mathrm{shift}}_b+1} \right\rceil \times (t^{\mathrm{shift}}_b+1).$$

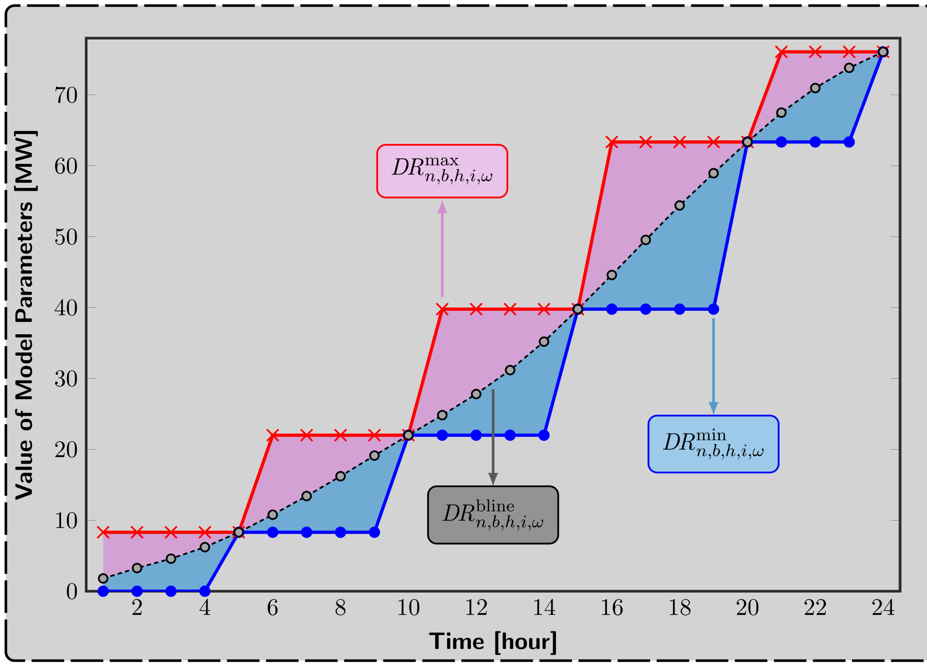

Fig. 4. DLC module parameters: $DR^{\mathrm{bline}}_{n,b,h,i,\omega}$, $DR^{\min}_{n,b,h,i,\omega}$, and $DR^{\max}_{n,b,h,i,\omega}$.

For the first shift window, the values of $DR^{\min}$ are set zero. Note that the last shift window in each season should be closed even if its length is less than *t.shift* to prevent the seasonal shift of energy in the system.

3.2.2. Mathematical formulation of DLC module in EMPIRE

This section presents the mathematical formulation of the DLC module and provides further insights into the distinctions between RLGs and ESSs in EMPIRE. Similar to ESSs, where the state of charge is calculated for each operational period, the DLC module in EMPIRE requires tracking the total activated DLC until the end of each operational period to properly model the t.shift of RLGs. This is accomplished through the following constraints:

$$w^{\mathrm{stor}}_{n,b,h,i,\omega} = \eta^{\mathrm{chrg}}_b y^{\mathrm{chrg}}_{n,b,h,i,\omega} - y^{\mathrm{dischrg}}_{n,b,h,i,\omega} + DR^{\mathrm{maxRed}}_{n,b,h,i,\omega} : \quad n \in \mathcal{N},\ b \in \mathcal{B}^{\mathrm{DR}}_n,\ h = h^1_s,\ s \in \mathcal{S},\ i \in \mathcal{I}, \omega \in \Omega, \tag{6}$$

$$w^{\mathrm{stor}}_{n,b,h,i,\omega} = w^{\mathrm{stor}}_{n,b,h-1,i,\omega} + \eta^{\mathrm{chrg}}_b y^{\mathrm{chrg}}_{n,b,h,i,\omega} - y^{\mathrm{dischrg}}_{n,b,h,i,\omega} + DR^{\mathrm{maxRed}}_{n,b,h,i,\omega} : \quad n \in \mathcal{N},\ b \in \mathcal{B}^{\mathrm{DR}}_n,\ h \in \{h^2_s, \dots, |\mathcal{H}_s|\},\ s \in \mathcal{S},\ i \in \mathcal{I}, \omega \in \Omega, \tag{7}$$

where Eq. (6) represents the first hour of a season and Eq. (7) represents the remaining hours. In Eqs. (6) and (7), the term $DR^{\mathrm{maxRed}}_{i,b,h,\omega}$ is an additional component compared to the energy balance equation of ESSs. This addition is made to distinguish between RLGs and ESSs and to indicate that loads deviate from their base load profiles. If the values of both upward and downward DLC activation (i.e., $y^{\mathrm{chrg}}_{n,b,h,i,\omega}$ and $y^{\mathrm{dischrg}}_{n,b,h,i,\omega}$, respectively) remain zero throughout a season, the variable $w^{\mathrm{stor}}_{n,b,h,i,\omega}$ accumulates the base load profile ($DR^{\mathrm{maxRed}}_{i,b,h,\omega}$) and follows $DR^{\mathrm{bline}}_{i,b,h,\omega}$. Consequently, at each hour, the difference between $w^{\mathrm{stor}}_{n,b,h,i,\omega}$ and $DR^{\mathrm{bline}}_{i,b,h,\omega}$ yields the total activated DLC and the recovery.

The hourly upward and downward deviations (load increment and reduction) from the RLG's base load profile are respectively limited to the corresponding maximum potential of increase and decrease as below:

$$0 \le y^{\mathrm{chrg}}_{n,b,h,i,\omega} \le DR^{\mathrm{maxDis}}_{n,b,h,i,\omega} : \quad \forall_n \in \mathcal{N}, \forall_b \in \mathcal{B}^{\mathrm{DR}}_n, \forall_h \in \mathcal{H}_s,\ s \in \mathcal{S}, \forall_i \in \mathcal{I}, \forall_\omega \in \Omega, \tag{8}$$

$$0 \le y^{\mathrm{disch}}_{n,b,h,i,\omega} \le DR^{\mathrm{maxRed}}_{n,b,h,i,\omega} : \quad \forall_n \in \mathcal{N}, \forall_b \in \mathcal{B}^{\mathrm{DR}}_n, \forall_h \in \mathcal{H}_s,\ s \in \mathcal{S}, \forall_i \in \mathcal{I}, \forall_\omega \in \Omega. \tag{9}$$

Unlike the State of Charge (SOC) of ESSs that is restricted to its energy capacity, for an RLG, the variable $w^{\mathrm{stor}}_{n,b,h,i,\omega}$ has no direct limitation. This variable is employed to model the shift windows through the following constraints:

$$\begin{cases} w^{\mathrm{stor}}_{n,b,h,i,\omega} \le DR^{\max}_{n,b,h,i,\omega} & : b \notin \mathcal{B}^{\overline{\mathrm{DR}}}_n \\ w^{\mathrm{stor}}_{n,b,h,i,\omega} \le DR^{\mathrm{bline}}_{n,b,h,i,\omega} & : b \in \mathcal{B}^{\overline{\mathrm{DR}}}_n \end{cases} : \forall_n \in \mathcal{N}, \forall_b \in \mathcal{B}^{\mathrm{DR}}_n, \forall_h \in \mathcal{H}_s,\ s \in \mathcal{S}, \forall_i \in \mathcal{I}, \forall_\omega \in \Omega, \tag{10}$$

$$\begin{cases} w^{\mathrm{stor}}_{n,b,h,i,\omega} \ge DR^{\min}_{n,b,h,i,\omega} & : b \notin \mathcal{B}^{\overline{\mathrm{DR}}}_n \\ w^{\mathrm{stor}}_{n,b,h,i,\omega} \ge DR^{\mathrm{bline}}_{n,b,h,i,\omega} & : b \in \mathcal{B}^{\overline{\mathrm{DR}}}_n \end{cases} : \forall_n \in \mathcal{N}, \forall_b \in \mathcal{B}^{\mathrm{DR}}_n, \forall_h \in \mathcal{H}_s,\ s \in \mathcal{S}, \forall_i \in \mathcal{I}, \forall_\omega \in \Omega. \tag{11}$$

At the end of each shift window, all activated DLC must be adjusted; therefore, $DR^{\min}_{n,b,h,i,\omega}$ and $DR^{\max}_{n,b,h,i,\omega}$ must be equal as is ensured by (4) and (5).

In Fig. 4, with the explanation provided in the prior paragraph as a backdrop and according to Eqs. (10) and (11), the variable $w^{\mathrm{stor}}_{n,b,h,i,\omega}$ can take values in the following regions:

1. Both pink and blue regions for RLGs that can be both advanced and delayed
2. Only pink region for advancing-only RLGs
3. Only blue region for delaying-only RLGs

4. Numerical results

This section reports and analyzes the results. The focus is mostly on the impact of residential DLC programs on long-term investment planning. However, the short-term operation of a few nodes for specific scenarios and investment periods is also investigated in the Appendix.

4.1. Implementation of DLC programs for residential sectors: The benefit

The total system cost for each case is summarized in Table 4, where total system costs include both investment and operational costs. The

Table 4
Total system cost improvement with DLC (excluding associated costs with DLC – **(P0)**) compared to Base Case.

Parameter	Case studies				
	Base case	Case I	Case II	Case III	Case IV
Total Cost [EUR]	2.199×10^{12}	2.193×10^{12}	2.187×10^{12}	2.181×10^{12}	2.177×10^{12}
Improve Percentage	–	0.25%	0.55%	0.80%	0.97%

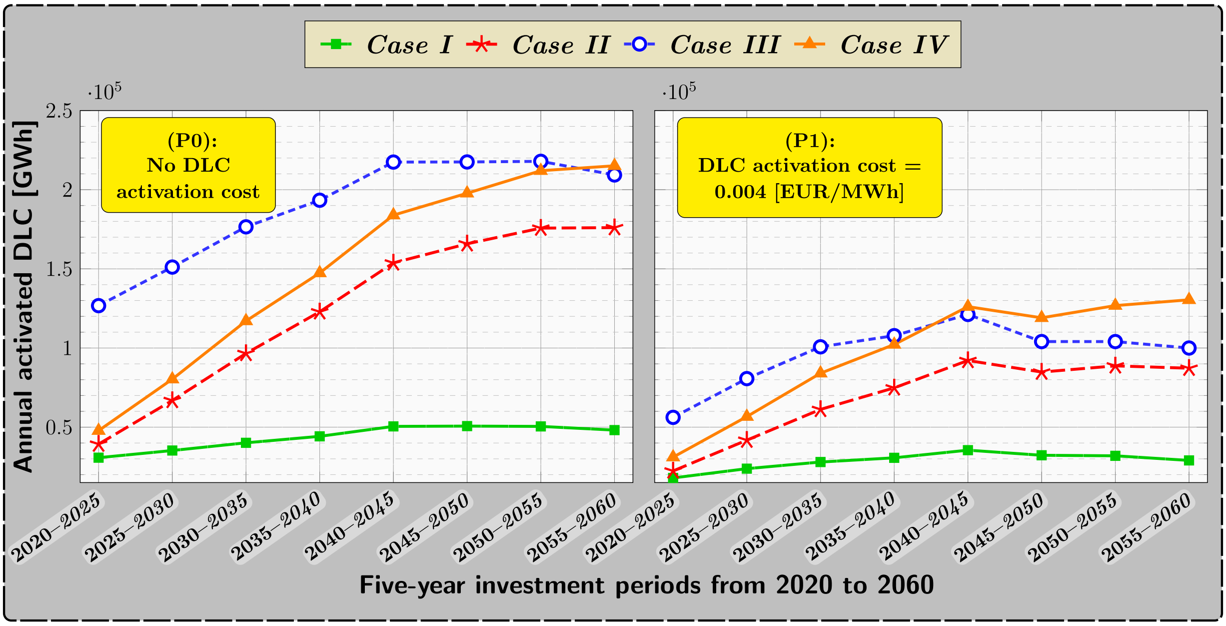

Fig. 5. Activated DLC for all case studies during each investment period.

results belong to **(P0)**, where costs related to DLC were disregarded. This represents the upper limit of cost improvement achievable with residential DLC programs. Compared to the base case, **Case I(P0)**, in which the participation rates are fixed, yields the smallest cost reduction (−0.25%), and **Case IV(P0)**, with doubled shift times and incremental participation rates, provides the highest cost reduction (−0.97%). Cost reductions range from 5.42 billion EUR to 21.4 billion EUR. By neglecting DLC costs, these cost reductions represent the savings in the European electricity system due to the availability of residential DLC. Note that there could be more savings related to DLC that is not captured by the modeling scope of EMPIRE.

4.1.1. Activated DLC in various case studies

This section compares the activated DLC in different storylines and investment periods. The activated DLC refers to the responsive loads that have been either delayed or advanced.

Fig. 5.a shows the annual activated DLC for all storylines without DLC activation cost **(P0)**. As can be seen in Fig. 5.a, the annual activated DLC in each case follows the trend of the DLC potential (input data) in the corresponding case. In **Case I(P0)**, the participation rates were assumed to remain fixed; therefore, the activated DLC, in this case, is not as large as in the other case studies. The increase in activated DLC in **Case I(P0)** is due to the increase in load profiles over time. **Case II(P0)** and **Case IV(P0)** experiences a large increase in the activated DLC over time. The reason is the increment in the participation rates over time. In **Case III(P0)**, full residential load participation in DLC programs leads to the highest annual activated DLC during all investment periods except the last one. In the eighth investment period (i.e., '2040–2045'), the annual activated DLC in **Case IV(P0)** surpasses that of **Case III(P0)**. The participation rates in **Case IV(P0)** during this investment period is less than **Case III(P0)** (see Fig. 2). However, the shift times considered doubled. Comparing these two cases reveals the importance of shift times.

As mentioned earlier, no cost was considered for DLC activation in the first set of case studies. To this end, in some situations, the responsive loads may be activated without any benefit to the system. This, for example, may occur when the marginal prices are fixed for several consecutive hours. As discussed in Section 3.2, to phase out this from the activated DLC, a very small cost (0.004 EUR/MWh) is assigned for the activation of responsive loads. Fig. 5.b shows the results for **Cases I–IV(P1)**. Although the objective function remained almost the same, the activated DLC decreased significantly. It is thus necessary to consider this small penalty if the value of the annual activated DLC will be used for post-analysis and policy making. Fig. 5.b provides a clearer emphasis on the significance of shift times compared to the previous case. Notably, even with considerably lower participation rates, the total activated DLC in **Case IV(P1)** surpasses that of **Case III(P1)** during the fifth investment period. Further analysis regarding activated DLC by considering DLC activation costs is provided in Section 4.6.

As a final point in this section, we have evaluated the ratio between the activated DLC and the total load in each node of the system. Fig. 6 shows the ratio between activated DLC and the total load for all countries for two investment periods: (a) investment period '2020–2025' in **Case I(P1)**, and (b) investment period '2050–2055' in **Case IV(P1)**. Note that Bosnia and Herzegovina, Macedonia, and Serbia were excluded from this figure because no DLC data was available for these countries. According to the results, France, Germany, Great Britain, and Italy have the highest activated DLC. This is consistent with the magnitude of the DLC potentials. The activated DLC in Germany exceeds the activated DLC in France in **Case IV(P1)** in the investment period '2050–2055', while France has higher activation in **Case I(P1)** during the investment period '2025–2025'. This is justified by taking a look at the participation rates in these two cases. The participation

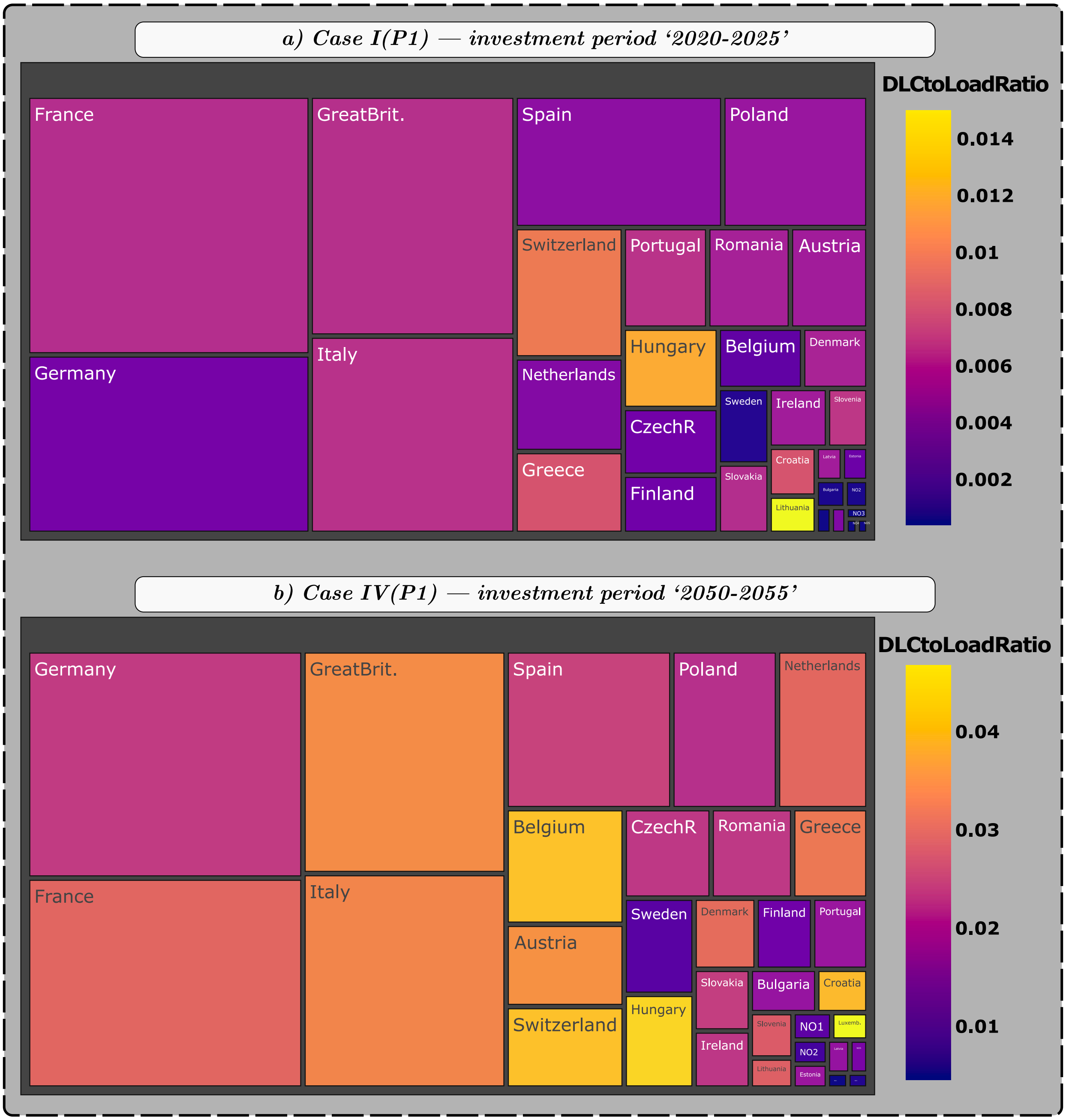

Fig. 6. Annual activated DLC during two investment periods. The size of the boxes is a relative indication of the value of activated DLC in different countries. Various colors indicate the ratio between annual activated DLC and the total annual load in each country. Note that the activated DLC in Norway is shown for five regions.

rates of various appliances in France are higher in the provided data (Section 2.1). However, the share of loads that participate in DLC programs in **Case IV(P1)** increases annually, and the participation rates of countries with lower initial values grow faster according to the description of this storyline. This explains the reason that the activated DLC in Germany exceeds France in **Case IV(P1)** during the investment period '2050–2055'.

Another important observation from Fig. 6 is the ratio between DLC and total load. According to the results, the activated DLC reaches a little higher than 1.4% of the total load during the investment period '2020–2025' in **Case I(P1)**. This value increases to about 4.5% in **Case IV(P1)** during the investment period '2050–2055'. **Case IV(P1)** is an ambitious storyline for residential DLC programs in European electricity system. Even in this case, this rate exceeds 3.5% for a few countries which reveals a limitation of this study: The DLC dataset only includes the residential sector.

4.2. Impact of residential DLC programs on generation investments

In this section, we investigate the impact of DLC programs on the capacity expansion of generation resources during all investment periods. Note that the energy storage devices will be discussed later in a separate section.

Fig. 7 shows the result of the EMPIRE modeling framework for the installed capacity of various generation resources in the European electricity system from 2020 to 2060. The implementation of residential

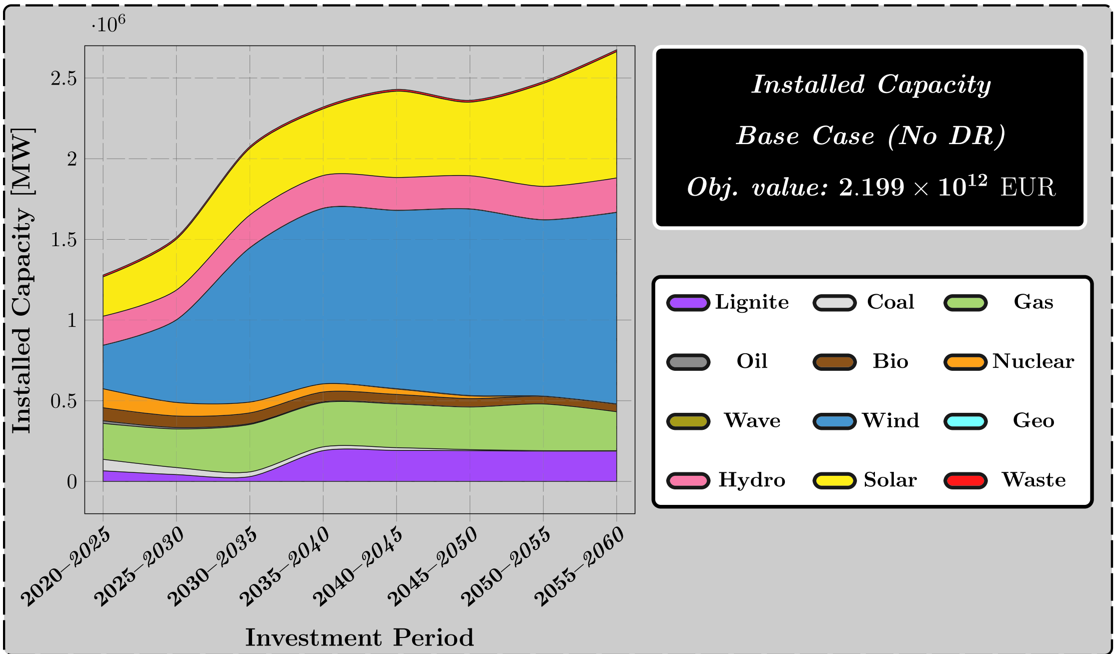

Fig. 7. European energy transition: Installed capacity of various resources during 2020–2050 without residential DLC programs (**Base Case**).

DLC programs makes no visible change in this figure. The same figure but for **Case IV(P0)** can be found in the Appendix (Fig. 18). The annual production of different power generation technologies can also be found in the Appendix in Fig. 19.

In order to investigate the impact of residential DLC programs on the installed capacity of various resources, differences between all the case studies with DLC and the **Base Case** have been calculated and shown in Fig. 8.a for the investment period '2050–2055'. In addition, Fig. 8.b shows the differences between the cases with DLC and the **Base Case** in terms of the annual production of various generation types for the same investment period. To enhance clarity, some generation types, including oil, nuclear, and geo, were excluded from the figure, as their differences were insignificant. The most salient observation from the figure is that, in all four cases, a portion of the wind and lignite generation is being substituted with PV production, and this substitution increases as the potential of responsive loads rises from **Case I(P0)** to Case IV(P0). These substitutions result from the interaction of various factors within the system, encompassing the potential for demand response, the intermittency and availability of both PV and wind energy, the investment and operational costs associated with different resources, as well as the CO2 emission limit, all of which contribute to system optimization with a focus on cost minimization. Notably, PV production is heavily influenced by sunlight availability. With increased responsive load potential, the system can strategically shift demand to periods when PV generation is more abundant (typically during daylight hours). This shift in demand can reduce the need for electricity from other sources, leading to reduced wind and lignite generation, which is the most cost-effective option. In some cases, the increase in the amount of PV generation, particularly in **Case IV(P0)**, exceeds the decrease in wind and lignite-based power generation. Additionally, there is a minor increase in waste and bio-based power production, which is compensated by a decline in coal, gas, wave, and Hydro-based generation. Although the reduction of investments in lignite is small in some cases, the corresponding decrease in its expected generation is substantial, indicating that the installed lignite capacity has higher utilization. Concluding this section, it is noteworthy that the overall changes in installed generation capacities is minimal, accounting for less than 0.5%.

4.3. Impacts of residential DLC programs on investments in the storage systems

The EMPIRE modeling framework derives the optimal investments in generation resources, energy storage systems, and transmission lines. An important question is then "*Which of these elements is influenced the most by the implementation of residential DLC programs?*" The short answer is energy storage systems, more specifically li-ion batteries. This is not surprising since responsive loads provide similar functionality to energy storage systems: They shift the loads from one time period to another time period.

Fig. 9 shows the annual discharge of li-ion batteries and their installed capacity. As can be seen, the annual discharge consistently follows the trend in installed capacity in all cases. The figure shows that implementing residential DLC programs in the European electricity system effectively decreases the usage of li-ion storage devices. The reliance on the li-ion batteries decreases as the DLC potential increases from **Case I(P0)** to **Case IV(P0)**. In **Case IV(P0)**, the annual discharge of the li-ion storage devices is close to zero until 2050. Nevertheless, during the last two investment periods, even **Case IV(P0)**, which includes an ambitious amount of available residential responsive loads, requires the installation of li-ion batteries since the penetration of VRES is very high. Note that for all cases, the investment in the capacity and charging/discharging rate of li-ion batteries follows the same trend as the annual expected discharge of li-ion batteries for all cases.

4.4. Impacts of residential DLC programs on investments in cross-border transmission

This section briefly examines the impact of DLC programs on transmission lines. All case studies that include DLC programs show a decrease in the total investment in transmission lines compared to the **Base Case**, as shown in Fig. 10.a. This reduction in investment

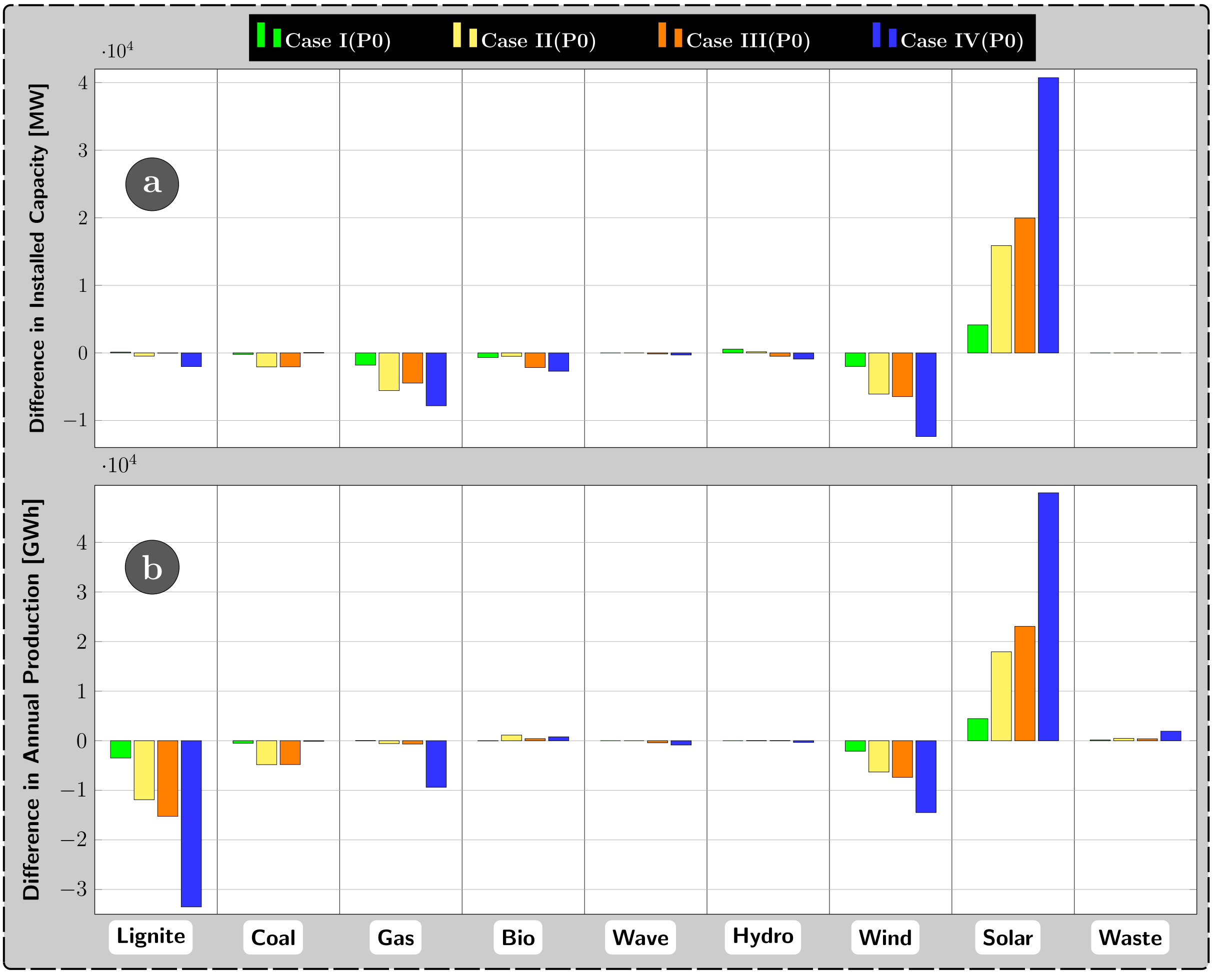

Fig. 8. Changes in installed capacities and annual production of various generation resources in the 7th investment period (2050–2055).

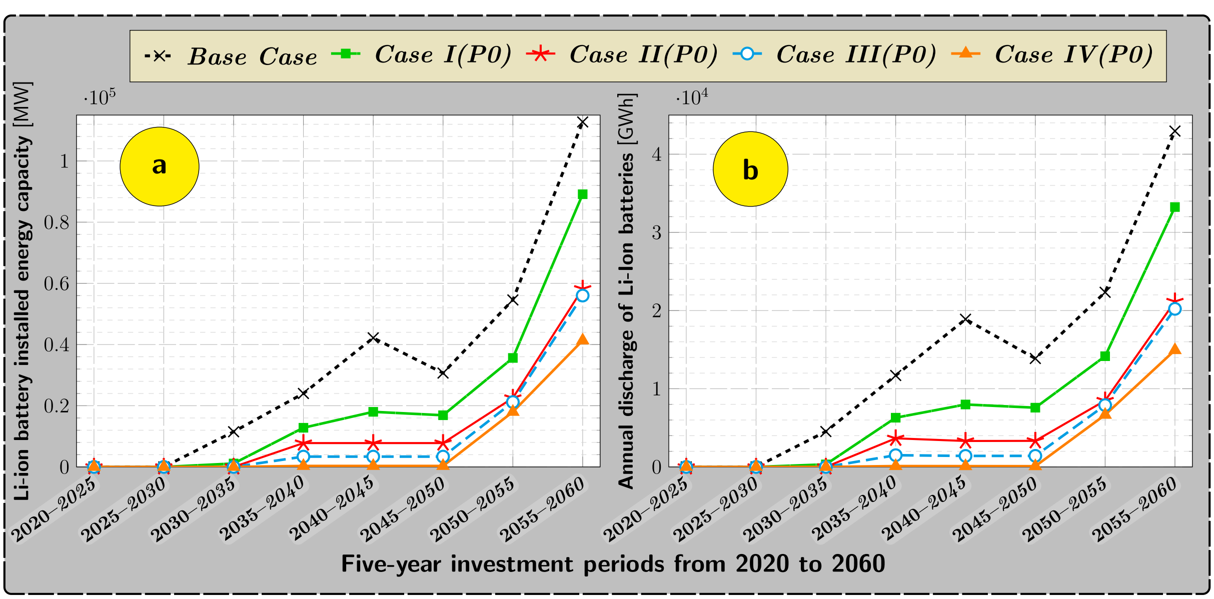

Fig. 9. Li-ion batteries: (a) Installed energy capacity, and (b) Annual expected discharge of Li-Ion batteries.

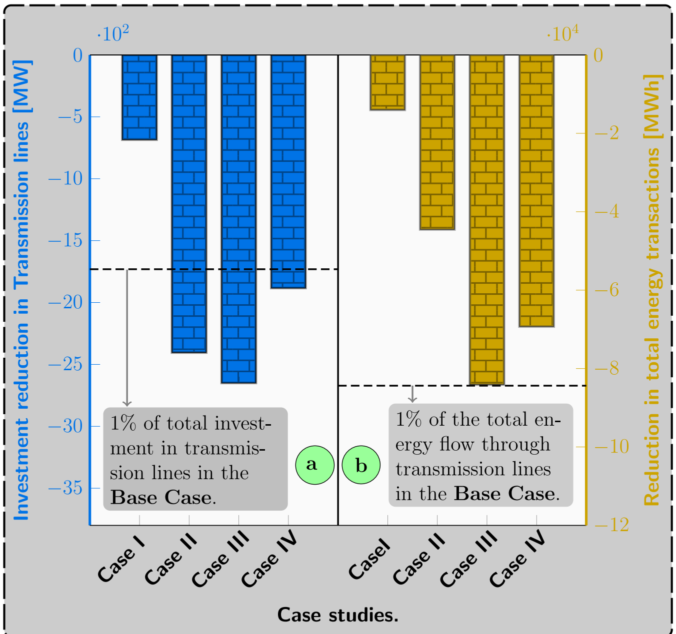

Fig. 10. Impact of residential DLC programs on the transmission lines: (a) investments, and (b) transferred energy.

increases as the flexibility potential increases from **Case I(P0)** to **Case III(P0)**. However, although **Case IV(P0)** has the lowest total cost, it achieves a smaller reduction in transmission line investments. This is because the smallest total cost depends on the combination of investments in ESSs, generation resources, and transmission lines as a whole, and not necessarily on the smallest investment in transmission lines alone. To fully comprehend why this occurs, it is essential to analyze investments in all nodes and investment periods, which is beyond the scope of this study.

Fig. 10.b shows the reduction in total energy transferred through transmission lines. The trend in total transferred energy follows that of the related investments. However, when comparing **Case II(P0)** and **Case IV(P0)**, **Case II(P0)** shows a smaller reduction in transferred energy compared to its reduction in investment. This is due to two reasons. Firstly, the reduction in investment in **Case II(P0)** occurs in later investment periods. Secondly, the usage of transmission lines is more efficient in **Case IV(P0)**.

4.5. Impact of residential DLC programs on hourly marginal costs

The value of lost loads is generally high [41]; therefore the load interruption incurs a high cost to the system. In EMPIRE, the load shedding cost is 22 000 EUR/MWh in the initial investment period, meaning that the occurrence of load shedding in a particular hour increases the hourly marginal cost of the corresponding hour to 22 000 EUR/MWh. The value is then discounted for subsequent investment periods using the discounting rate of 0.05, as considered in this study. Fig. 11.b shows the hourly discounted peak prices during each investment period for all case studies. As can be seen in this figure, the maximum hourly marginal cost during periods '2025–2030', '2035–2040', and '2035–2040' is equal to load shedding cost in some cases, indicating that load interruption occurred. This is also confirmed in Fig. 20 in the Appendix. In some cases, the implementation of DLC programs can effectively decrease the maximum hourly marginal cost of certain periods, as seen in Fig. 11.b. During the first two investment periods, **Case III(P0)** performs better than other cases as it includes the maximum theoretical DLC potential. After some periods, **Case IV(P0)** performs better in diminishing the peak prices since the DLC potential increases in this case over time, and the shift windows were considered doubled in this case compared to **Case I(P0)**. However, an observation from this figure is the increase in peak prices for some cases with DLC programs, indicating that the DLC programs do not necessarily guarantee the reduction in peak prices in all investment periods.

The average price per MWh for all case studies is presented in Fig. 11.a. The results indicate that the implementation of DLC programs may not necessarily lead to a decrease in the average price per MWh for all investment periods. For example, during the sixth investment period (245–2050), **Cases I(P0)**, **II(P0)**, and **III(P0)** have a higher average price per MWh compared to the **Base Case** without DLC programs. Similarly, **Case IV(P0)** reduces the average price per MWh for all investment periods except for the fourth period.

4.6. DLC activation cost

In the case studies presented thus far, the cost of payment to the flexible loads has not been factored in. However, based on the insights gained from the set of case studies with a small DLC activation cost **(P1)**, our current objective is to investigate the average present value of DLC activation in the European electricity system, considering residential DLC programs. By combining the saving with the total activated DLC in each case study, we can calculate the average present value of DLC as follows:

$$AveragePresentValueOfDLC\,[\text{EUR/MWh}] = \frac{NetPresentSaving\,[\text{EUR}]}{TotalActivatedDLC\,[\text{MWh}]}, \tag{12}$$

Considering a small activation cost **(P1)**, the $AveragePresentValueOfDLC$ values for **Case I-IV(P1)** are 4.7, 4.4, 4.6, and 5.5 [EUR/MWh], respectively. Assuming an overall average of 5 [EUR/MWh], the impact of the payment cost on residential DLC programs is being investigated by conducting three additional sets of case studies: at 50%, 100%, and 400% of this value. Overall, the following sets of case studies are analyzed in this section:

- **(P0):** DLC activation cost = 0 [EUR/MWh]
- **(P1):** DLC activation cost = 0.004 [EUR/MWh]
- **(P2):** DLC activation cost = 2.5 [EUR/MWh]
- **(P3):** DLC activation cost = 5 [EUR/MWh]
- **(P4):** DLC activation cost = 20 [EUR/MWh]

The outcomes for the average present value of DLC and the DLC to load ratio across all case studies are depicted in Fig. 12. It is evident that an increase in the activation cost of the DLC in the model leads to a decrease in the total amount of activated DLC, as the decision to activate DLC is determined by its cost-effectiveness. The reduction in the total activated DLC is reflected in the DLC to load ratios depicted in Fig. 12. This decline is noticeable across all storylines. For instance, in **Case III**, when the activation cost is 0.004 EUR/MWh, the DLC to load ratio is approximately 2.1%. However, this ratio decreases significantly to only 0.26% when the DLC activation cost is elevated to 20 EUR/MWh.

Conversely, as seen in this figure, the average present value of DLC, calculated through (12), increases with higher DLC activation costs. This trend is attributed to load shifting, which occurs when it offers a higher value due to the associated increased cost. Additionally, other observations can be drawn from the presented data. Firstly, the average present value of DLC is quite consistent across case studies that have similar activation costs. Secondly, when comparing **Case IV** to **Case III** while considering DLC activation costs, the DLC to load ratios in **Case IV** exceed those in **Case III**, despite the higher participation rate of responsive loads in **Case III**, which highlights the significance of shift times.

The percentages of total cost reductions in all case studies are shown in figure Fig. 13. Note that the set of case studies with no

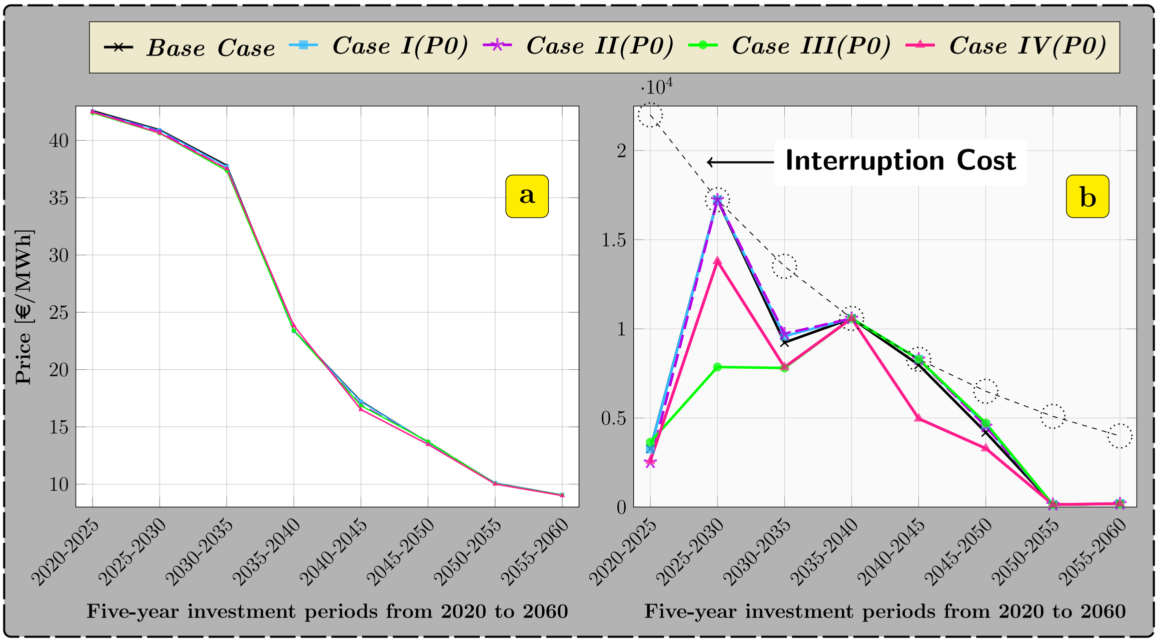

Fig. 11. Impact of residential DLC programs on discounted marginal prices: (a) Average price per MWh and (b) Hourly Peak price during each investment period.

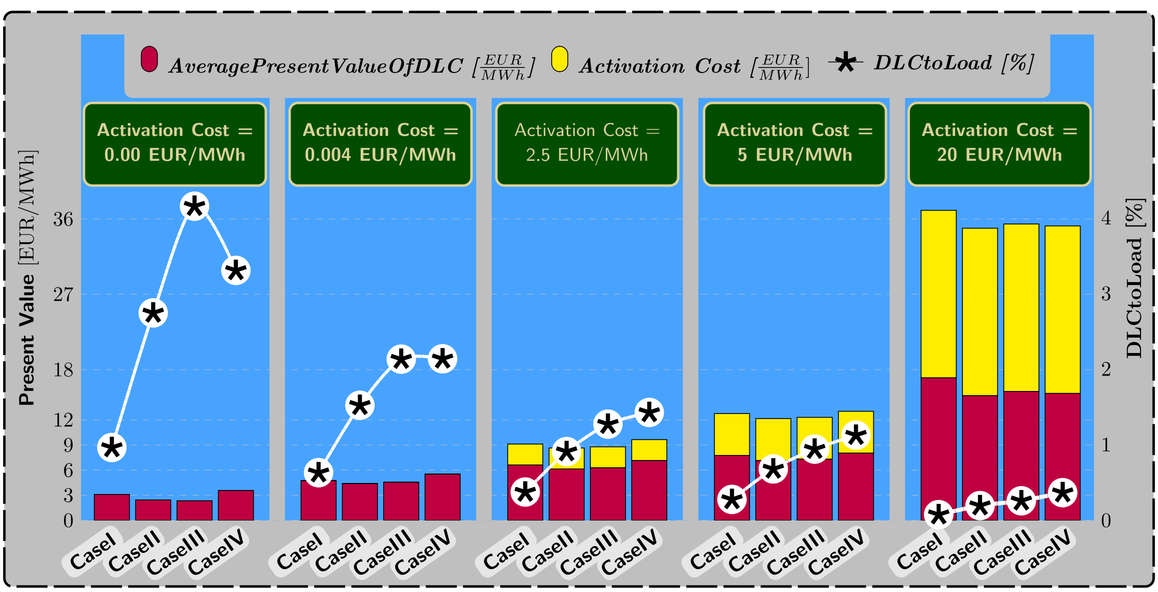

Fig. 12. Comparison of the average present value of DLC and the DLC to Load ratio across all case studies.

activation cost yields nearly the same level of cost reduction as the one with an activation cost of 0.004 [EUR/MWh]. The outcomes reveal a large decrease in overall savings as the DLC activation costs increase across all storylines. In the most optimistic storyline, which involved an ambitious participation rate for responsive loads, the exclusion of DLC activation costs, and the assumption of doubled shift times compared to the original DLC dataset, a reduction of 0.97% in the total system cost was observed. However, it is crucial to note that achieving this level of savings through the implementation of a residential DLC program in the European electricity system appears unattainable due to the assumptions made in this case. This underscores the modest impact, which is below one percent, that can be achieved through the implementation of a residential DLC program.

Concluding this section, the impact of DLC activation costs on the investment decisions for ESSs is investigated. Fig. 14 shows the installed energy capacity of lithium-ion battery storage devices under case studies with DLC activation costs of 2.5 and 20 [EUR/MWh]. It can be observed that, as the DLC activation cost increases, a greater portion of the investment is directed towards lithium-ion battery storage systems. With a 20 [EUR/MWh] activation cost, the system, even in **Case IV**, is required to start investing in li-ion batteries as early as 2035. However, a reduction in the overall deployment of li-ion batteries remains a noteworthy aspect in all cases.

5. Conclusion

This study examined the impact of residential DLC programs on long-term investment strategies within the European electricity system from 2023 to 2060. This analysis considers several critical aspects, including the long-term investment perspective, short-term operational

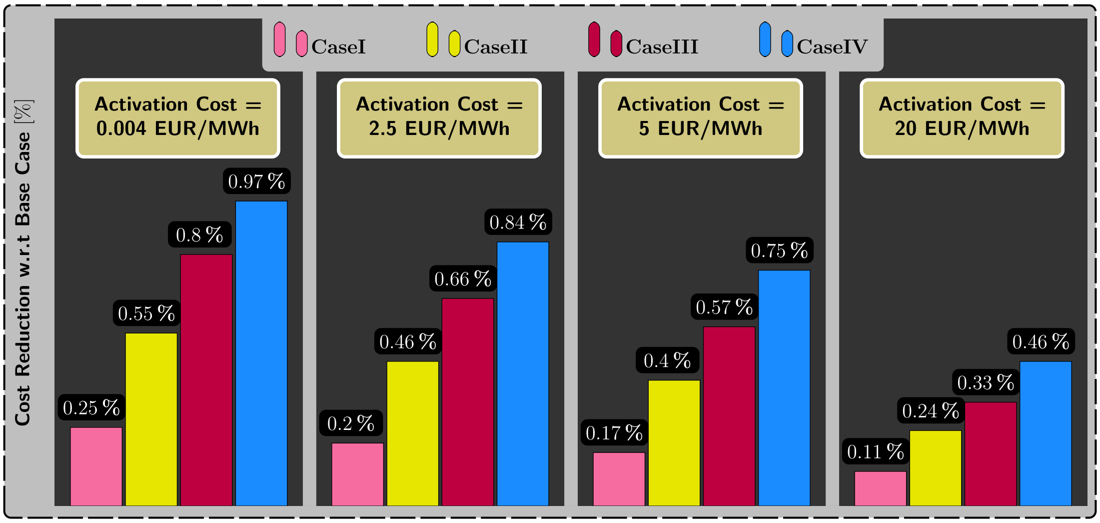

Fig. 13. Net present cost reduction through residential DLC program implementation across all case studies.

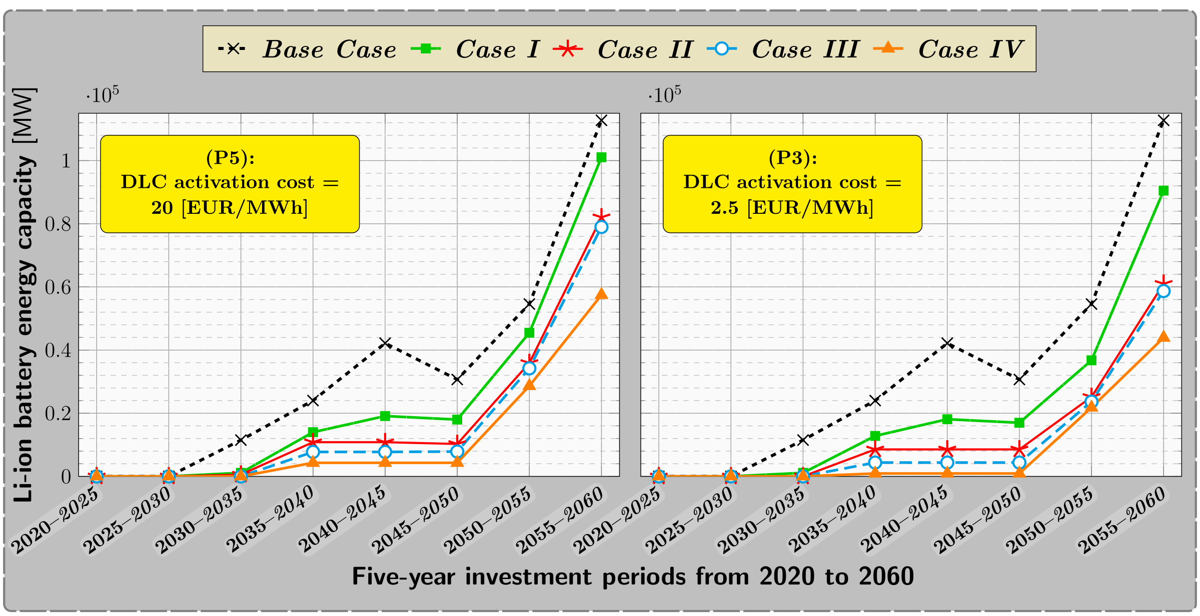

Fig. 14. Installed energy capacity of lithium-ion battery storage systems considering the impact of DLC activation costs.

factors, and endogenous uncertainty. For this purpose, we utilize a comprehensive residential DLC dataset, estimating the DLC potential for ten appliances across European countries until 2050. This dataset forms the foundation for constructing four storylines related to the incorporation of these programs into the European electricity system. To bring these storylines to life, we utilized the open-source EMPIRE modeling tool and further developed the DLC module within this tool, providing a robust framework for exploring the potential outcomes and implications of incorporating residential DLC programs within the European context.

The examination of diverse case studies showed a limited impact resulting from the implementation of DLC programs, particularly concerning generation capacity expansions and cost savings. The best-case scenario, involving an ambitious participation of responsive loads in DLC programs without compensation and a doubling of the shift times compared to the original values in the DLC dataset, resulted a reduction of 0.97% in the total cost of the system. However, it is important to acknowledge that achieving this improvement may not be attainable due to the assumptions made in this specific scenario. The cost savings for a scenario featuring the original participation rates and shift times in the DLC dataset, along with a DLC activation cost of 20 [EUR/MWh], amounted to only 0.11%. Concerning the expansion of generation resources, the adoption of DLC programs facilitated a greater penetration of PV units; nonetheless, the overall impact was fairly minor, accounting for less than 0.5%. On the other hand, the results indicated that implementing DLC programs could decrease the need for Li-Ion batteries. The reduction in the total installed energy capacity of li-ion storage devices about 28% in the worst case scenario with a DLC activation cost of 20 [EUR/MWh].

However, there is still room for improvement in this study. Specifically, we need to pursue further research in four areas. Firstly, the method we used to model the shift windows has a limitation, as it cannot account for flexible DLC activation. With the modeling framework presented in this paper, responsive loads can only shift during specific,

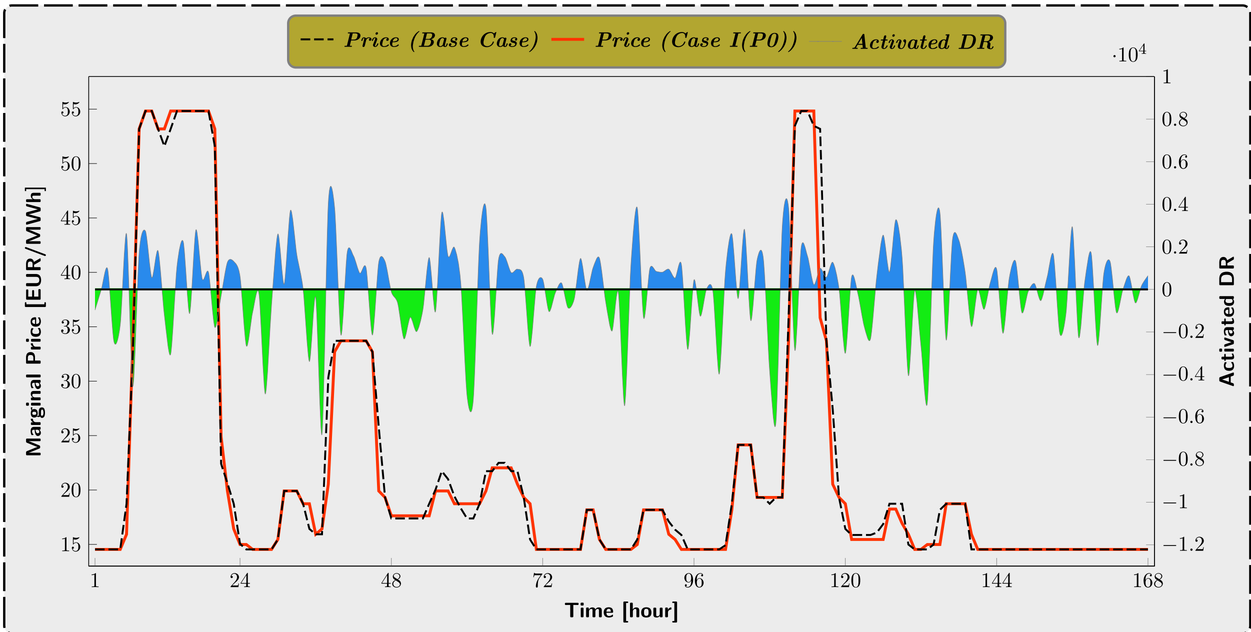

Fig. 15. Short-term activity of responsive loads in Germany during a winter week in investment period '2050–2055' for **Case I(P0)**.

fixed time windows. This approach may underestimate the potential impact of responsive loads. To address this, we increased the *t.shift* of all RLGs in one of our case studies, which showed that shift windows have a major impact on the results. Therefore, it is crucial to revise the DLC module to incorporate flexible shift windows and fully exploit the potential of these programs. We are working towards addressing this point in our future work.

Secondly, as the results showed, the amount of activated DLC relative to the total load in the system was low even for ambitious scenarios. Therefore, it would be interesting to explore other load sectors, such as commercial and industrial sectors, in future studies.

Lastly, the characteristics of DLC programs both in terms of load shift duration and frequency of events will vary given local built environments, climates, and thermal comfort preferences. Future, efforts will focus on capturing this heterogeneity and building more robust estimates of pan-European residential DLC contribution to decarbonizing the energy system.

CRediT authorship contribution statement

Mostafa Barani: Conceptualization, Methodology, Software, Validation, Writing – original draft, Data curation. **Stian Backe:** Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Ryan O'Reilly:** Methodology (DLC dataset), Data curation (DLC dataset), Writing – original draft, Writing – review & editing. **Pedro Crespo del Granado:** Conceptualization, Supervision, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The input data and scripts are publicly available; refer to version 1.1.0 of EMPIRE (Access link).

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Appendix

A.1. Analysis of short-term operation

As the final point regarding the result derived by the EMPIRE modeling framework, the short-term operation of the system is investigated through two sample weeks. Fig. 15 shows the DLC activity and the hourly marginal prices of a winter week in Germany during the investment period '2050–2055' for **Case I(P0)**. As can be seen in this figure, the activity of responsive loads follows the marginal prices of the system for most of the hours. Therefore, the activation of DLC could flatten the marginal prices to some degree. In this sample week, the mean of the hourly marginal prices decreases by 1.2%.

This reduction in the mean of the hourly marginal prices is not always the case. The marginal prices in each node (representing a country or region) also depend on other nodes. In addition, the marginal prices may increase during the hours that the load increases due to load shifts. Therefore, some sample weeks in some nodes and scenarios may experience even an increase in the mean of the hourly marginal prices when DLC programs are included. As an example, Fig. 16 shows another sample week belonging to a summer week in Spain during the investment period '2025–2030'. During this week, the mean of the hourly marginal prices increased by 0.85% when the residential DLC program was included (**Case IV(P0)**). Further, since no cost was assigned to the activation of responsive loads, the responsive loads may be activated without any benefit. This can be seen in Fig. 17, which shows the short-term activity of the same week for **Case IV(P1)**.

A.2. Installed capacity of all available technologies in Case IV(P0)

See Fig. 18.

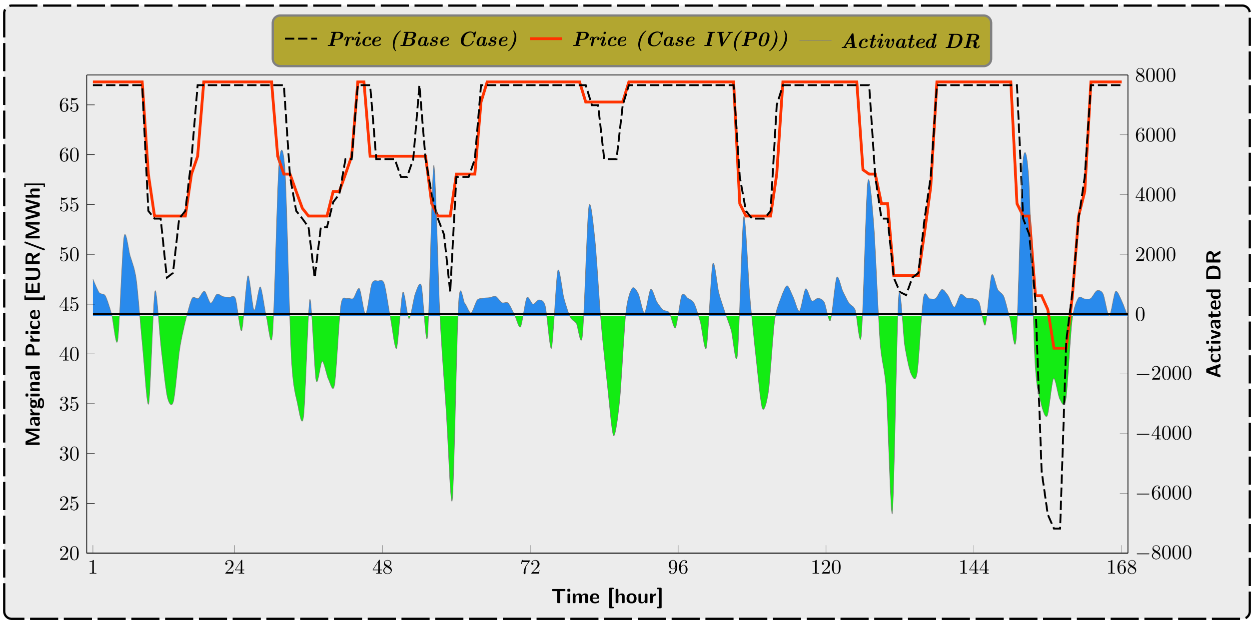

Fig. 16. Short-term activity of responsive loads in Spain during a summer week in investment period '2025–2030' for **Case IV(P0)**.

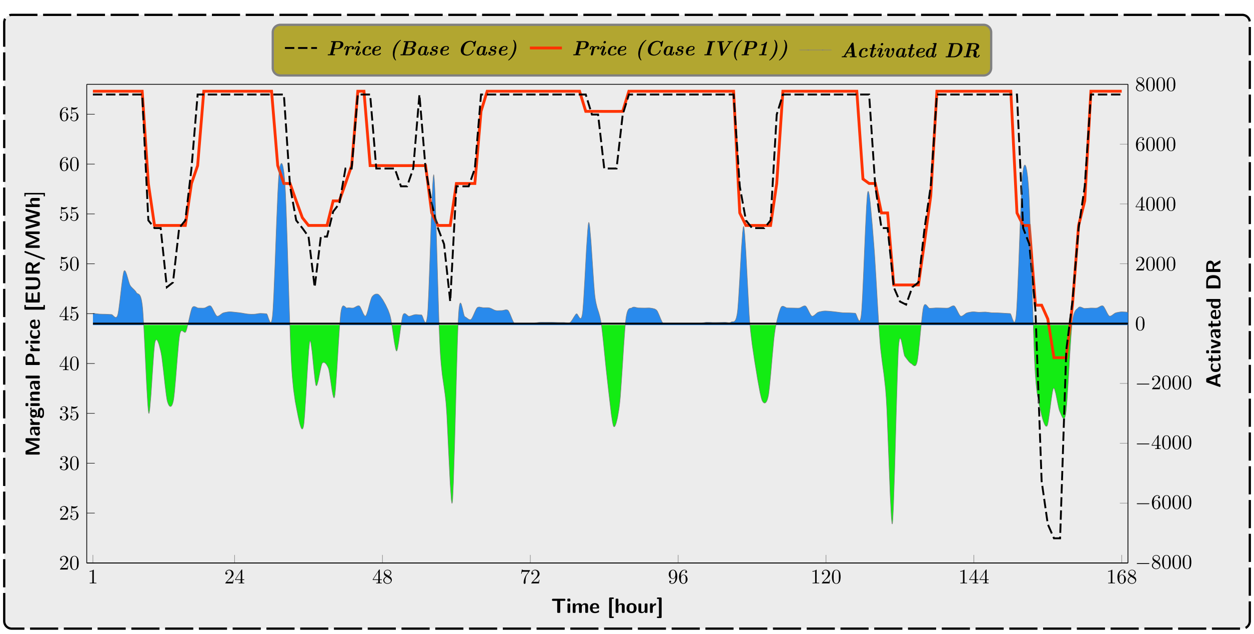

Fig. 17. Short-term activity of responsive loads in Spain during a summer week in investment period '2025–2030' for **Case IV(P1)**.

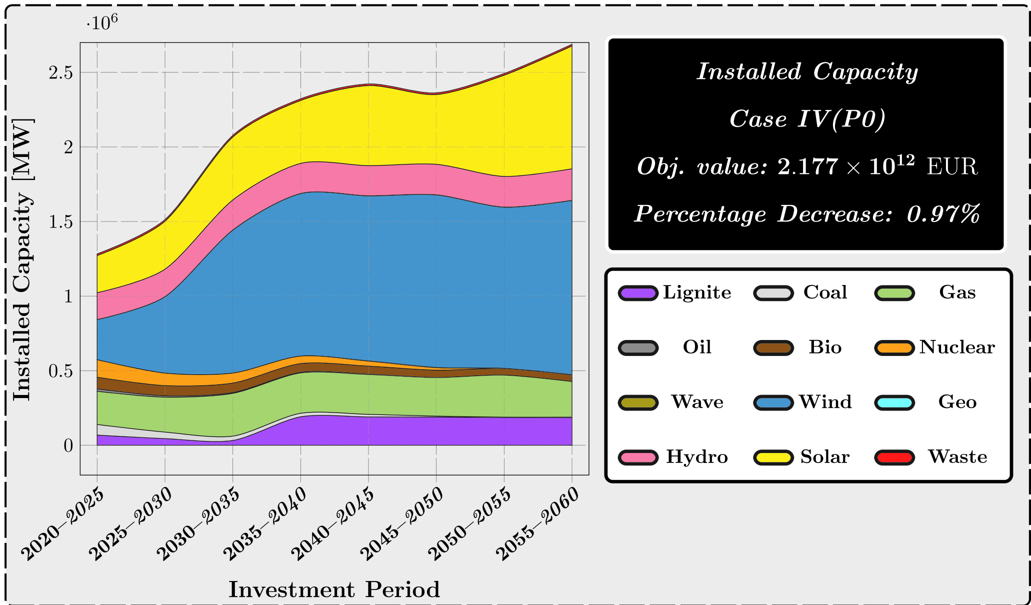

Fig. 18. European energy transition: Installed capacity of various resources from 2020 to 2050 with residential DLC programs (Case IV(P0)).

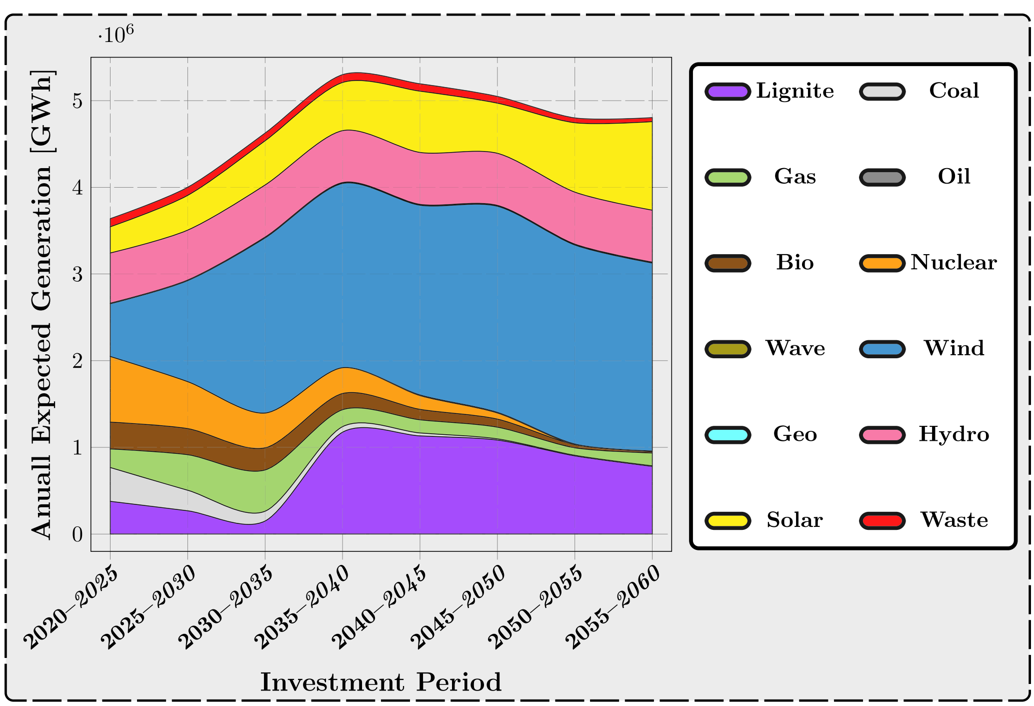

Fig. 19. Annual Expected Generation of various resource in the **Base Case**.

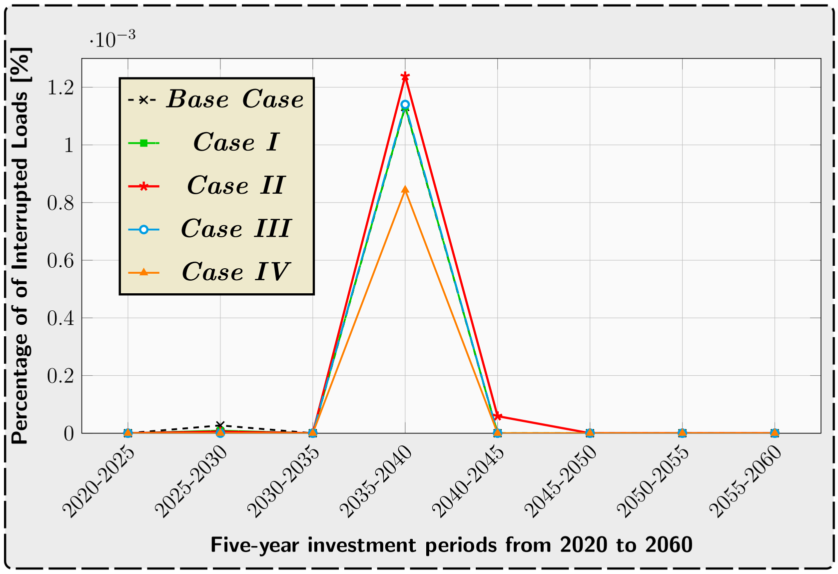

Fig. 20. Percentage of interrupted loads for all case studies – (P0).

Table 5
Participation Rates of DLC program by household device and result type.

Publication	Study type	Wash	Ref	AC	WH	Heat	EV	Other
AEG [31]	Hypothetical			22%	23%	4%		6%
Broberg and Persson [42]	Hypothetical	44%				44%		
Spence et al. [43]	Hypothetical	49%	30%		52%			
Mert and Tritthart [44]	Hypothetical	93%	96%					
ETSA Utilities [45]	Real			14%				
Eto et al. [46]	Real			3%				
Bode et al. [47]	Real			7%				
Sullivan et al. [48]	Real			8%				
Kofod [49]	Real					10%		
Sullivan et al. [48]	Real			18%				
Sullivan et al. [48]	Real			38%				
VTT [50]	Real				50%			
Xu et al. [51]	Hypothetical			67%				
Buckley et al. [52]	Real							10%
Yilmaz et al. [53]	Hypothetical	26%			58%	57%	27%	
Stenner et al. [54]	Hypothetical				13%			
Annala et al. [55]	Hypothetical	80%		80%	80%			
Annala et al. [55]	Hypothetical							74%
Tarroja and Hittinger [56]	Hypothetical						64%	
Tarroja and Hittinger [56]	Hypothetical						48%	
Yilmaz et al. [53]	Hypothetical					62%	60%	
Average DR Participation - Adjusted		26%	28%	18%	25%	17%	22%	15%

A.3. Annual expected generation of all available technologies in the base case

See Fig. 19.

A.4. Percentage of interrupted loads for all case studies in EMPIRE

See Fig. 20.

A.5. DLC participation rates

Table 5 below shows the estimated participation rate for the studies and pilots identified in our literature review.

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