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The effect of price-based demand response on carbon emissions in European electricity markets: The importance of adequate carbon prices

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ABSTRACT

Price-based demand response (PBDR) has recently been attributed great economic but also environmental potential. However, the determination of its short-term effects on carbon emissions requires the knowledge of marginal emission factors (MEFs), which compared to grid mix emission factors (XEFs), are cumbersome to calculate due to the complex characteristics of national electricity markets. This study, therefore, proposes two merit order-based methods to approximate hourly MEFs and applies them to readily available datasets from 20 European countries for the years 2017–2019. Based on the calculated electricity prices, standardized daily load shifts were simulated which indicated that carbon emissions increased for 8 of the 20 countries and by 2.1% on average. Thus, under specific circumstances, PBDR leads to carbon emissions increases, mainly due to the economic advantage fuel sources such as lignite and coal have in the merit order. MEF-based load shifts reduced the mean resulting carbon emissions by 35%, albeit with 56% lower monetary cost savings compared to price-based load shifts. Finally, by repeating the load shift simulations for different carbon price levels, the impact of the carbon price on the resulting carbon emissions was analyzed. The Spearman correlation coefficient between carbon intensity and marginal cost along the German merit order substantially increased with increasing carbon price. The coefficients were -0.13 for the 2019 carbon price of 24.9 €/t, 0 for 42.6 €/t, and 0.4 for 100.0 €/t. Therefore, with adequate carbon prices, PBDR can be an effective tool for both economical and environmental improvement.

1. Introduction

1.1. Motivation

High penetrations of variable renewable energy sources (vRES) in national electricity grids are essential to achieve the global aims of the Paris agreement. Price-based demand response (PBDR) is a promising approach, especially in smart grids, to provide the operational flexibility, that is needed for the integration of vRES. Due to the characteristics of the electricity market, available approaches used for carbon emissions accounting lead to misleading results when applied in the context of demand response (DR). Specifically, they overestimate the environmental potential of PBDR by ignoring the nature of the electricity markets and their special phenomenon called the merit order dilemma of emissions. This phenomenon refers to the fact that, for electricity generation, certain emission-intensive fuel types are, due to their low marginal costs, preferred to relatively lower emission-intensive technologies. At the time of writing, for example, highly efficient combined-cycle gas power plants, are, according to the merit-order dispatch principle, only considered after more carbon-intensive lignite-fired power plants. Adequate approaches based on the idea of MEs, require detailed data, which are usually not available. As a consequence, as long as the merit order of an energy market does not correlate with the carbon emission factors, PBDR cannot exploit the full carbon reduction potential of load shifting. In the European Union (EU), spot market prices already include a carbon price within the EU Emissions Trading System (ETS), however this carbon price is currently too low to make a substantial impact on PBDR. Increasing the carbon price to an appropriate level is crucial to exploit this potential by internalizing the external cost of climate change and creating financial incentives for sustainable development [1].

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Nomenclature

Acronyms/abbreviations

CC	Combined-Cycle
CEF	Carbon Emission Factor
CONV	Conventional energy sources
DR	Demand Response
EDRM	Empirical Data & Relationship Models
ETP	ENTSO-E Transparency Platform
ETS	Emissions Trading System
GHG	Greenhouse Gas
ME	Marginal Emission
MEF	Marginal (power plant) Emission Factor
PBDR	Price-Based Demand Response
PP	Power Plant method to calculate carbon emission factors
PSOM	Power System Optimization Models
PWL	Piecewise-Linear approximation method to calculate carbon emission factors
PWLv	Validation variant of PWL method
RES	Renewable Energy Sources
vRES	variable Renewable Energy Sources
XE	Grid Mix Emission
XEF	Grid Mix Emission Factor

Indices/sets

$f \in F$	Generation fuel types
$p \in P$	Power plants
$t \in T$	Timesteps

Symbols

Δt	Time-step-width in hours
η^{T}	Constant transmission efficiency considering all transmission and distribution losses
η_p^{el}	Generation efficiency per power plant p
$\gamma_{t,p}^{\mathrm{m}}$	Binary indicator of marginal unit
$\gamma_{t,p}^{\mathrm{x}}$	Capacity utilization rate per time step t and power plant p
ε	Carbon emissions
$E_{t,f}^{\mathrm{gen}}$	Generated energy per fuel type f and time step t in MWh
P_p^{inst}	Installed power plant capacity per power plant p in MW

1.2. Background

The integration of additional vRES requires an increase in the operational flexibility of the electricity grids to compensate for the increasing fluctuation of the residual load, which defines the total load minus the production from vRES. Operational flexibility in this context means that it is not based on structural changes in the electricity system such as power station commissioning/decommissioning or fuel price changes [2]. This flexibility can be provided by flexible generation, interconnection, energy storage, and demand-side resources [3]. PBDR is seen as an essential and promising approach for unlocking the flexibility potential of demand-side resources in a cost-efficient way [4]. Thus, PBDR has been the subject of many recent studies across the residential, commercial, and industrial sectors, as shown in the review articles [5–8]. Also, PBDR can be combined with incentive-based DR as demonstrated in [9].

For the quantification of electricity-related carbon emissions, the temporal granularity of CEFs is important. Annual average CEFs, which are still commonly used, lead to inaccurate results because of the high variance of emission factors of different fuel types. This is even more important for the evaluation of emissions due to load changes such as with PBDR. Several studies, therefore, suggest the usage of time-varying CEFs instead of yearly average CEFs for short and long term decision making [10–12].

Dynamic average electricity mix emission factors (XEFs) are useful for calculating carbon emission balances of energy consumers. Since it is usually not possible to trace electricity from a specific producer to consumer, the average carbon intensity of the entire generation system is attributed to each customer [13]. However, if XEFs are used to assess or reduce the real effect of DR on carbon emission, the results may be misleading [14,15]. The reason for this is that not all power plants react proportionally to a change in demand [14]. In theory, the electricity requested will come from the power plant with the lowest marginal cost and spare capacity, the so-called marginal power plant [16]. Dynamic marginal (power plant) emission factors (MEFs) estimate the carbon intensity of demand changes as the carbon intensity of the marginal power plant for each time step [14]. This is why, if the real impact of DR on operational carbon emissions is to be determined or even minimized, MEFs should be used where possible. However, the calculation of hourly MEFs requires a very detailed database, which is why hourly MEFs are not available for most areas [15]. As a consequence and despite a growing body of literature that recognizes the necessity of MEFs for assessing the environmental effects of PBDR [11,14,15,17–22], XEFs are still used in this context.

Through PBDR, price incentives and potential savings that arise in an energy spot market by varying supply and demand of electricity are passed on to the energy consumer. However, energy spot markets lead, under perfect competitions, to a cost-minimizing dispatch, which, depending on the correlation between prices and emissions along the merit order, may lead to a suboptimal dispatch in an environmental sense. This phenomenon is known as the merit order emission dilemma as illustrated in [17].

The fluctuating feed-in of vRES significantly affects the carbon emissions of the electricity supplied to consumers. In times of high vRES shares, the carbon emissions per produced unit of electricity are usually lower than in times of lower vRES shares since less fossil-based power plants per produced unit of electricity are in operation. This phenomenon leads to the hypothesis that a shift of energy consumption from an hour with a low vRES share to an hour with a high vRES share leads to a decrease in carbon emissions. In fact, a calculation according to XEFs, which describes the current generation mix of the electricity system supports this hypothesis in many cases, e.g., [12,23,24]. However, price-based or XEF-based load shifting might lead to increased emissions as illustrated in Fig. 1.

One option to minimize carbon emissions through load shifting is the usage of MEFs instead of prices as a primary DR incentive signal, as Leerbeck et al. [25] suggest. Real-time MEFs with resolutions between 5 and 15 min are already commercially available via application programming interfaces from companies such as WattTime [26] or Tomorrow [27]. However, since prices and emissions along the merit order are not fully correlated, cost minimization and emission minimization are conflicting. As a second option, this cost-emission conflict can be resolved by internalizing the external costs of climate change by placing an adequate price on carbon emissions. Both options will be analyzed in this study.

In summary, fuel type specific, temporally resolved national generation data (e.g., from the ETP [28]) allows for the calculation of temporally resolved XEFs which are necessary for carbon emissions accounting of electric consumers. However, for the environmental evaluation of PBDR activities like load shifting, dynamic MEFs are needed, since they reflect the effects of system changes, which XEFs do not. Due to the lack of power plant specific electricity generation data,

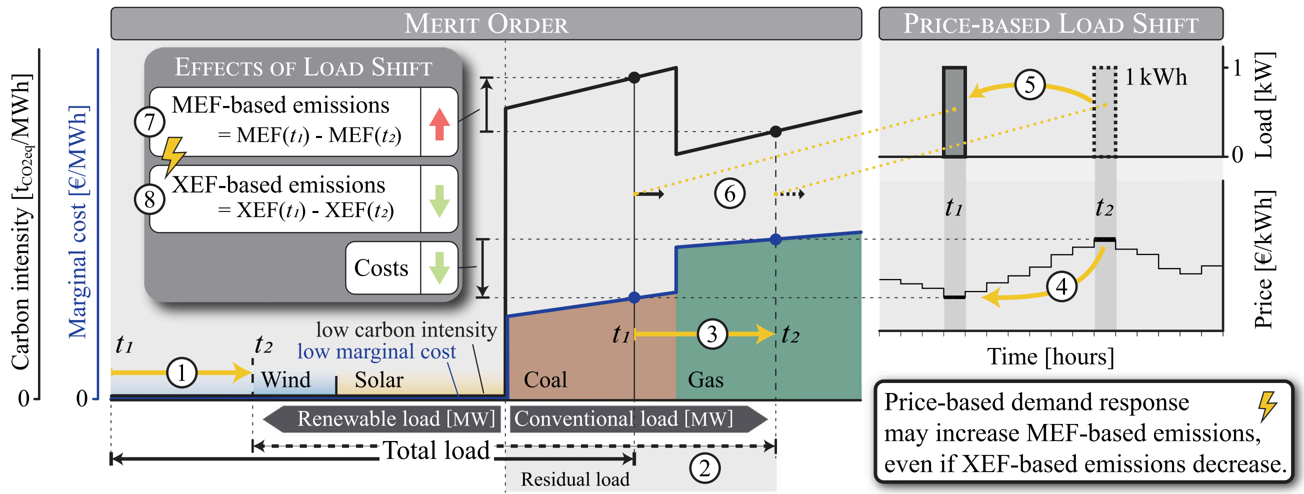

Fig. 1. Exemplary case where price-based or XEF-based load shifting leads to increased total emissions: We assume two hours t_1 and t_2, with the same loads but different levels of wind generation ①. In t_2, less wind implies a higher residual load ②, thus, a different operating point in the merit order curve ③. This causes a price spread in the spot market ④ which incentivizes a load shift of 1 kWh from t_2 to t_1 ⑤. The power plant that increases production is coal-fired in the load shifting scenario and gas-fired in the non-load-shifting scenario ⑥. Since the MEF at t_1 is higher than the MEF at t_2, the load shift causes increased MEF-based emissions ⑦. In contrast, the XEF is lower at t_1 than at t_2, since at t_2, coal and gas substitute the reduced wind. Therefore, in this example, using XEFs to quantify the effect of the load shift is misleading as it actually results in increased carbon emissions ⑧.

the purely empirical identification of the marginal power plant is not straightforward [29]. As a consequence, to the best of the authors' knowledge, dynamic historic MEFs are not available free of charge for European countries.

1.3. Literature review

In the literature, essentially there are two dimensions to classify electricity grid CEFs. The methodology dimension classifies the methods behind the CEFs into Empirical Data & Relationship Models (EDRM) such as regression analyses and Power System Optimization Models (PSOM) such as economic dispatch models [30]. The other dimension divides the CEFs according to their CEF-type into XEFs and MEFs. XEFs describe the current generation mix of the electricity system and account for RES shares while MEFs quantify marginal system effects [17].

The methodology behind XEFs is an attributional approach where all emissions of the electricity grid in a particular time frame are shared across all electricity consumers in proportion to their demand [11]. This prevents double counting of emissions and is therefore often used in the context of carbon accounting [32]. The XEFs are determined by weighting the power plant type specific carbon emissions with its share of total electricity consumption during each hour. Therefore, it reflects the current state of the electricity mix, e.g., the share of renewable and conventional electricity production [17].

The marginal power plant method to calculate MEFs focuses on the element of the power plant mix that will actually be affected by changes on the demand side and reflect the consequences on carbon emissions of the electricity system [41]. In uniform-pricing markets, power plant owners are incentivized to bid at their individual marginal cost. This merit order sorts all power plants according to their marginal costs. A load reduction or increase within a specific hour is now compensated by an increased power output of the marginal power plant. The MEF is therefore equal to the specific emission factor of the marginal power plant.

Ryan et al. [30] provides a useful guideline for selecting the most appropriate method. For a review of carbon emission accounting approaches in electricity generation systems, the reader is referred to the work of Khan [22].

Within the literature, different approaches for the determination of CEFs can be found. Table 1 shows an overview of studies clustering them by type, methodology, temporal and geographic scope, and temporal resolution into three groups.

Studies in Group A calculated historic, hourly or half-hourly XEFs with EDRMs for different countries. Most of these studies [10,12,23,24,31–35] focus on calculating simple emission factors for either individual or a few countries by weighting the historic generation data with the according carbon emission factors per fuel type. Tranberg et al. [18] proposed a more sophisticated approach. Using flow-tracing which allows the tracking of power flows on the transmission network from the region of generation to the region of consumption they calculated consumption-based XEFs for 27 European countries. The results show significant deviations between the consumption-based and the generation-based XEFs and suggest to include cross-border flows for carbon emission accounting of electricity. This method is demonstrated in the electricityMap [42], which is a real-time visualization of the carbon emission footprint of electricity consumption. However, they do not focus on MEFs as we do.

For Group B, Hawkes published a seminal work in 2010 [14]. Using half-hourly data from the UK for 2002–2009, he calculated the first difference of system carbon emissions and system load, respectively, and determined the average MEF by the slope of the regression line of the two difference vectors. Compared to purely merit-order based methods, this has the advantage that it implicitly takes into account the trading decisions of the players in the market, the logistical constraints of power plant operation, and transmission and distribution restrictions. However, the nature of statistical relationship models restricts these methods in the temporal resolution of the resulting MEFs which is significant for assessing DR measures. The regression can be performed repeatedly on subsets of the data to obtain, e.g., time-of-day or time-of-year MEFs as also shown by subsequent studies following Hawkes' approach by applying it to different geographic regions [15,20,37,38] but this still neglects important information such as the fluctuating RES share. Through the comparison of XEFs and MEFs, Siler-Evans et al. [15] found that XEFs may misestimate the emissions that can be avoided from an demand-side intervention. Pean et al. [21] extended Hawkes' approach by clustering the data of Spain in the year 2016 according to system load and RES share and then realizing a linear regression on every cluster. By fitting a quadratic function of RES share and system load to the results of the regression they were able to

Table 1
Classification of studies that propose methods to calculate electricity CEFs according to type, methodology, scope, and temporal resolution. The studies are clustered in three groups and within these sorted by years. The two characteristics of methodology refer to Empirical Data & Relationship Models (EDRMs) and Power System Optimization Models (PSOMs) proposed by Ryan et al. [30].

	Study			CEF type		Methodology		Scope		Temporal
	Year	Name	Ref.	XEF	MEF	EDRM	PSOM	Temporal	Geographic	resolution of CEFs
Group A	2014	Stoll et al.	[24]	•		•[a]		Historic: 2011, 2012	UK, SE, US	Hourly
	2014	Messagie et al.	[31]	•		•[a]		Historic: 2011	BE	Hourly
	2016	Roux et al.	[32]	•		•[a]		Historic: 2013	FR	Hourly
	2017	Kono et al.	[33]	•		•[a]		Historic: 2011–2015	DE	Hourly
	2017	Kopsakangas-S. et al.	[12]	•		•[a]		Historic: 2011	FI	Hourly
	2017	Summerbell et al.	[23]	•		•[a]		Historic: 2015	UK	Half-hourly
	2018	Khan et al.	[10]	•		•[a]		Historic: 2015	NZ	Half-hourly
	2019	Clauß et al.	[34]	•		•[a]		Historic: 2015	NO, SE, DK, FI	Hourly
	2019	Munné-Collado et al.	[35]	•		•[a]		Historic: 2018	5 European countries	Hourly
	2019	Tranberg et al.	[18]	•		•[b]		Historic: 2017	27 European countries	Hourly
Group B	2010	Hawkes	[14]	•	•	•[c]		Historic: 2002–2009	UK	Time-of-day/year
	2010	Greensfelder et al.	[36]	•	•	•[c]		Historic: 2008	US (4 regions)	Hourly
	2012	Siler-Evans et al.	[15]	•	•	•[c]		Historic: 2006–2011	US (8 regions)	Time-of-day/year
	2014	Thomson	[37]	•	•	•[c]		Historic: 2008–2013	UK	Time-of-day/year
	2017	Pareschi et al.	[20]	•	•	•[c]		Historic: 2015	AT, CH, DE, FR	Annual
	2017	Thomson et al.	[38]	•	•	•[c]		Historic: 2009–2014	UK	Time-of-day/year
	2018	Péan et al.	[21]	•	•	•[c]		Historic: 2016	ES	Hourly
Group C	2006	Bettle et al.	[39]	•	•		•[d]	Historic: 2000	UK	Half-hourly
	2018	Regett et al.	[17]	•	•		•[d]	Future: 2030	DE	Hourly
	2019	Baumgärtner et al.	[11]	•	•		•[d]	Historic: 2016	DE	Hourly
	2019	Böing & Regett	[40]	•	•		•[d]	Future: 2020–2050	DE	Hourly
	Our study			•	•		•[d]	Historic: 2017–2019	20 European countries	Hourly

[a]Simple Emission Factors.
[b]Flow Tracing.
[c]Statistical Relationship Model.
[d]Economic Dispatch Model.

compute hourly MEFs. Although this approach seems to be promising for our aim of comparing the environmental effect of DR for different countries, it involves constant emission factors per fuel type that disregards the efficiency differences of power plants within a fuel type which is of high significance for national energy systems that are based on one or two fuel types as, e.g., in Lithuania or Serbia.

Finally, studies in Group C computed historic or future MEFs in hourly or higher resolution using PSOMs, more precisely Economic Dispatch Models. Bettle et al. [39] used historic generation data per power plant of the UK for the year 2000 to calculate half-hourly MEFs that indicated up to 50% higher carbon emission savings than the XEFs. However, this method is not applicable to most of the European countries where power plant specific generation data are not readily available. Furthermore, they used fixed power plant efficiencies per fuel type. Regett et al. [17] computed future, hourly XEFs and MEFs for Germany and found that they are negatively correlated with each other meaning that they can lead to opposing results, which highlights the importance of the choice of CEF type. Based on [17], Böing & Regett [40] proposed an emission accounting method that determined dynamic XEFs and MEFs for different energy carriers in multi-energy systems. However, their focus laid on the future energy system for an individual country and not on the comparison of multiple countries based on historic data. Baumgärtner et al. [11] ran an economic dispatch model on German data of the year 2016 that resulted in hourly XEFs and MEFs which fed into a subsequent multi-objective synthesis problem of a low-carbon utility system. They used power plant specific efficiencies that were approximated by a logarithmic size-dependent regression of real power plants. However, the power plant sizes are not available for all countries and efficiencies also depend on the year of construction.

The importance of CEFs for the evaluation of demand side management based on carbon emissions is reflected in the broad range of scientific literature. However, as presented in Table 1, the literature focuses mainly on XEFs and single-country analyses which is a result of sparse data availability and heterogeneity of available data quality. Only a few studies calculate MEFs with hourly resolution and none of them compare hourly MEFs between different countries. To cope with the heterogeneity of the generation technology mixes in these countries, carbon effect analyses are necessary for each individual country. Therefore, the existing body of literature lacks an analysis of the effects of PBDR on carbon emissions for the major European markets using hourly MEFs.

1.4. Contribution

Within this work, we quantitatively analyze the effect of load shifting on carbon emissions in 20 European countries using hourly XEFs and MEFs. To overcome the barriers arising from the heterogeneous data quality, we propose a piecewise linear (PWL) method to approximate hourly MEFs based on the technology mix. We validate the PWL method with the power plant (PP) method which is applicable if detailed data on the generators are available. Since undesirable effects of price-based load shifts on carbon emissions can be observed, we investigate how this effect could be mitigated by an increase of carbon prices.

The novel contributions of this study are:

1. Quantitative comparison of the environmental effects of price-based, XEF-based, and MEF-based load shifting between 20 European countries using hourly XEFs and MEFs.
2. Proposal and validation of the PWL method which approximates MEFs and XEFs from datasets readily available for European countries.
3. Application of the PWL method to 20 European countries for the years 2017–2019 to compare the resulting CEFs.
4. Evaluation of the impact of varying carbon prices on the marginal cost–emission correlation, the merit order, and on the effects of load shifting.
5. Identification of the carbon price (42.6 €/t) which decouples the carbon intensities from costs in the German merit order.

The resulting hourly and quarter-hourly XEFs, MEFs, marginal costs, and marginal fuel types as well as residual load, total load and marginal

	AT	BE	CZ	DE	DK	ES	FI	FR	GB	GR	HU	IE	IT	LT	NL	PL	PT	RO	RS	SI
Hydro Pumped Storage	7.3	2.2	1.4	1.8	-	1.3	-	2.0	0.7	1.1	-	1.1	1.3	16.6	-	0.6	6.1	-	2.2	1.4
Fossil Peat	-	-	-	-	-	0.0	6.2	-	-	-	-	8.8	-	-	-	-	-	-	-	-
Fossil Coal-derived gas	-	-	1.9	-	-	0.0	-	-	-	-	-	-	2.3	-	-	0.4	-	-	-	-
Fossil Oil shale	-	-	-	-	-	0.0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Other	0.3	6.4	1.2	0.5	-	0.2	1.4	-	0.3	-	2.4	0.0	9.9	4.4	20.5	-	0.5	-	1.4	-
Other_conventional	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Fossil Oil	0.0	0.0	0.1	0.8	0.9	0.9	0.0	0.3	0.0	0.0	0.0	9.0	0.4	-	-	1.1	-	-	-	0.0
Fossil Gas	16.4	26.5	6.6	8.7	9.1	30.9	7.5	7.1	45.3	42.5	25.2	35.6	43.8	11.3	49.1	7.3	33.0	15.9	0.1	2.4
Fossil Hard coal	2.1	0.0	2.5	8.8	13.3	4.2	7.8	0.3	2.4	-	-	2.5	6.6	-	18.7	52.3	10.6	2.0	-	-
Fossil Brown coal/Lignite	-	-	39.3	20.2	-	0.2	-	-	-	26.2	13.5	-	-	-	-	25.9	-	21.7	68.1	27.0
Nuclear	-	46.8	35.4	14.0	-	22.4	38.1	71.0	20.9	-	51.2	-	-	-	4.4	-	-	19.2	-	37.2
Marine	-	-	-	-	-	0.0	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Hydro Water Reservoir	8.2	-	1.3	0.3	-	7.2	-	2.6	-	7.2	0.4	-	3.1	-	-	0.1	3.9	9.1	1.9	-
Hydro Run-of-river and poundage	45.1	0.1	1.0	2.9	-	3.5	19.0	7.6	1.4	-	0.3	3.5	13.3	10.2	0.0	1.0	10.6	17.6	26.0	29.2
Biomass	3.6	3.1	2.4	8.1	12.9	1.2	9.9	0.6	6.8	-	3.3	-	2.0	11.5	0.0	1.4	5.7	0.7	0.4	0.6
Waste	1.5	1.7	0.2	1.2	4.6	1.0	0.4	0.3	-	-	0.4	-	0.1	4.2	-	-	-	-	-	0.5
Geothermal	0.0	-	-	0.0	-	0.0	-	-	-	-	-	-	2.2	-	-	-	-	-	-	-
Other renewable	0.0	-	2.9	0.3	-	0.3	0.3	-	-	-	0.4	-	-	-	-	-	-	-	-	-
Wind Onshore	13.2	3.8	0.9	19.6	36.0	21.0	9.4	6.1	9.9	14.2	2.3	39.6	7.7	39.7	3.2	10.0	27.4	11.4	-	0.0
Wind Offshore	-	5.3	-	4.8	19.6	0.0	-	-	8.0	-	-	-	-	-	3.9	-	-	-	-	-
Solar	2.2	4.0	2.8	8.2	3.4	5.8	-	2.1	4.4	8.8	0.6	-	7.4	2.3	0.1	-	2.1	2.3	-	1.6

Share of annual electricity

(a) **Net electricity generation** (t, y, c, f). Here: Calculated shares of annual generation in %.

	AT	BE	CZ	DE	DK	ES	FI	FR	GB	GR	HU	IE	IT	LT	NL	PL	PT	RO	RS	SI
Hydro Pumped Storage	14.6	5.7	5.6	4.2	-	5.4	-	3.8	2.6	4.1	-	3.0	8.0	25.0	0.0	4.2	14.4	-	6.9	4.8
Fossil Peat	0.0	-	-	-	-	0.0	6.6	-	-	-	-	3.5	0.0	-	0.0	-	0.0	-	-	0.0
Fossil Coal-derived gas	0.0	-	1.8	-	-	0.0	-	-	-	-	-	-	1.9	-	0.0	0.6	0.0	-	-	0.0
Fossil Oil shale	0.0	-	-	-	-	0.0	-	-	-	-	-	-	-	-	0.0	-	0.0	-	-	0.0
Other	0.1	0.1	0.0	0.6	-	0.1	1.9	0.1	4.2	-	-	6.6	1.1	3.9	0.0	-	0.2	-	0.2	0.0
Other_conventional	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Fossil Oil	0.8	1.4	0.0	2.0	6.3	0.7	8.3	2.5	0.0	0.0	4.6	12.9	1.5	0.0	0.0	1.0	0.0	-	-	1.6
Fossil Gas	21.0	28.8	5.9	14.2	11.4	28.9	11.1	9.1	34.8	28.6	44.3	43.4	49.1	47.5	51.0	5.0	23.4	16.1	3.1	13.1
Fossil Hard coal	2.8	2.0	5.8	11.4	23.0	9.1	13.2	3.0	8.0	-	-	8.7	5.1	-	15.2	52.3	8.9	5.5	-	0.0
Fossil Brown coal/Lignite	0.0	-	40.6	9.5	-	0.0	-	-	-	22.8	11.5	-	0.0	-	0.0	18.8	0.0	16.4	60.3	24.7
Nuclear	0.0	25.6	19.4	4.3	-	6.8	16.1	48.3	8.9	-	20.9	-	-	-	1.6	-	0.0	6.9	-	18.6
Marine	0.0	-	-	-	-	0.0	-	0.2	-	-	-	-	0.0	-	0.0	-	0.0	-	-	0.0
Hydro Water Reservoir	11.5	-	3.6	0.6	-	18.3	-	6.3	-	14.0	0.3	-	4.1	-	0.0	0.4	7.7	17.9	3.7	0.0
Hydro Run-of-river and poundage	26.1	0.8	1.6	1.8	0.0	1.1	18.2	8.4	1.8	1.7	0.3	2.2	11.3	3.6	0.1	1.0	14.5	14.7	21.3	28.2
Biomass	2.3	3.1	1.9	3.5	10.9	0.5	10.5	1.5	3.9	0.3	2.7	-	1.6	2.7	1.6	2.0	3.1	0.6	0.1	0.5
Waste	0.7	1.6	0.5	0.8	2.4	0.5	0.9	-	-	-	0.6	-	0.1	0.6	2.5	-	0.0	-	-	1.1
Geothermal	0.0	-	-	0.0	-	0.0	-	-	-	0.0	0.0	0.2	0.9	-	0.0	-	0.0	-	-	0.0
Other renewable	0.2	-	1.9	0.2	0.9	0.2	1.5	-	1.8	0.4	0.8	-	0.0	0.0	0.0	-	0.0	-	-	0.0
Wind Onshore	14.2	9.7	1.5	23.7	27.9	21.9	11.7	10.4	12.2	13.7	3.6	19.5	10.2	14.6	12.0	13.7	26.1	15.8	4.3	0.1
Wind Offshore	0.0	6.7	-	2.9	10.7	0.0	-	0.0	9.0	-	-	-	0.0	-	3.1	-	0.0	-	-	0.0
Solar	5.6	14.6	9.8	20.4	6.4	6.4	0.0	6.3	12.8	14.2	10.3	-	5.0	2.3	12.9	1.0	1.6	6.1	0.0	7.4

Share of total installed generation capacity

(b) **Installed generation capacity** (y, c, f). Here: Share of total capacity in %.

Fig. 2. Overview of used data from ETP [28] per fuel type and country after preprocessing for the year 2019: (a) Net electricity generation and (b) Installed generation capacity. Blue fields with "-" indicate missing data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

power plant efficiency can be downloaded as CSV files for 20 European countries and the years 2017–2020 from GitHub.com/DrafProject/Marginal-Emission-Factors [43].

1.5. Paper organization

The remainder of this paper is structured as followed. First, all datasets used for the calculation of the CEFs are described in Section 2. Then, the methods for the CEFs calculation, PP and PWL, are detailed in Section 3. In Section 4, the PP method is applied to the power plant resolved dataset for Germany in 2019 to evaluate the approximation error of the PWL method. In Section 5, the PWL method is applied to the data of 20 European countries. First, the resulting merit order and CEFs are described, Section 5.1. In Section 5.2, cost–emissions correlations are analyzed. In Sections 5.3 and 5.4, load shifts based on prices, MEFs, and XEFs are simulated and the results discussed. In Section 5.5, the phenomenon of increasing carbon emission as effect of PBDR is explained using the results of six exemplary countries. In Section 5.6, a sensitivity analysis of carbon emissions on the merit order is conducted that demonstrates the impact of the carbon price on the merit order and the mitigation of the merit order dilemma of emissions. Section 5.7 summarizes the results and discussions and in Section 6, we conclude the findings of this paper.

2. Datasets used in this study

2.1. Net generation

For the calculation of the temporally resolved residual and total load of a national electricity system, historic electricity generation time series data ("Aggregated Generation per Type") for each fuel type f and country c from the ETP [28] were used and accessed via the entsoe-py client [44]. For the years 2017–2019 and the 20 countries used in this paper, 10.2 Million data points were processed. Across all European countries, 20 different fuel types are used for electricity generation. The temporal resolution of the raw data varies depending on the country (15, 30, and 60 min intervals). A comprehensive review of the data composition of the ETP can be found in [45]. Within the data preprocessing for the simulation, all time series were downsampled to hourly resolution. In the case of missing values and outliers, the last available data points were considered instead. The percentage of missing values that were filled were 1.9% for 2017, 1.3% for 2018, and 0.4% for 2019. However, 67% of the missing values appear in only two fuel types ('Fossil Hard coal' and 'Other') for the Netherlands for the years 2017 and 2018. Nine outliers were detected by a combination of z-score analysis and treated as missing values, see Supplementary Material E. To save space, the fuel types were renamed.[1] Fig. 2(a) shows the share of annual generation per fuel type and country in relation to the total generation for 2019 after preprocessing. Supplementary Material A and B contain basic analyses of available generation data from the ETP [28] for Europe and Germany, respectively.

2.2. Installed generation capacity

Installed electricity generation capacities per fuel type f were also obtained from the ETP [28]. The same renaming of fuel types as in Section 2.1 was conducted. Fig. 2(b) shows all preprocessed data for 2019 in a concise way. Supplementary Material A contains an overview of available installed generation capacity data on the ETP [28].

[1] Biomass → biomass, Fossil Brown coal/Lignite → lignite, Fossil Oil → oil, Fossil Gas → gas, Fossil Hard coal → coal, Hydro Run-of-river and poundage → hydro, Nuclear → nuclear

Table 2
Assumption of k^{cc} (share of combined-cycle gas turbines across all gas fueled power plants in %).

AT	99.57[b]	ES	94.73[b]	HU	32.80[b]	PL	100.00[b]
BE	80.92[b]	FI	100.00[b]	IE	71.76[b]	PT	93.26[b]
CZ	100.00[b]	FR	83.50[b]	IT	99.78[b]	RO	46.24[b]
DE	53.52[a]	GB	42.31[b]	LT	0.00[b]	RS	0.00[c]
DK	28.12[b]	GR	79.90[b]	NL	85.96[b]	SI	0.00[b]

[a]From the OPSD power plant list of the PP method [46].
[b]GEO list [47].
[c][48].

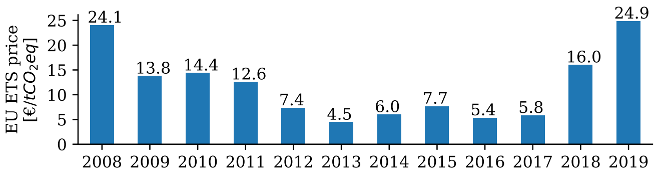

Fig. 3. Historic annual average CO_2-emission prices of the EU ETS for the years 2008–2019.
Source: [49].

2.3. Open Power System Data (OPSD) power plant list

For the PP method and to verify the PWL method with a higher granularity of generation capacity, the power plant list from the OPSD [46] was used. This data consists of 893 power plants for the electricity market region Germany, Austria and Luxembourg with 38 features each. The most relevant features were country, capacity, date for commissioning and shutdown, type, as well as efficiency estimate. In this paper, for the sake of simplicity, individually controllable power plant units are referred to as power plants. In Fig. 6, e.g., the nine light brown horizontally distributed dots near 20 GW represent the nine generation units of the Jänschwalde power plant which have similar characteristics. For the construction of the merit order, only active power plants were considered by constraining the year of simulation after date of commissioning and before shutdown. The distribution of efficiency and capacity can be seen in Supplementary Material C.

2.4. Global Energy Observatory (GEO) power plant list

Due to the particularly strong influence of power plant efficiency, power plants are further distinguished according to their technology type in open cycle gas turbines (indicated with gas) and combined-cycle gas turbines (indicated with gas_cc). The division into gas and gas_cc was based on k^{cc} which is the proportion of combined-cycle gas turbines in all gas power plants for each analyzed country. These shares were calculated from the GEO power plant list [47] with two exceptions: For Germany, the share was calculated from the OPSD list in favor of more detailed data. For Serbia, no gas power plants were listed on [47] at the time of data retrieval. Independent investigation identified its share to be $k^{cc} = 0\%$. All used values for k^{cc} are listed in Table 2.

2.5. Carbon emission certificate prices

In order to calculate the carbon-related marginal costs for the merit order, European Emission Allowances (EUA) prices of the European Union ETS are used from the European Energy Exchange (EEX) [49] (downloaded via [54]). The data was downsampled from weekly to annual resolution with average method and used in mean annual form as c^{GHG}, see Fig. 3.

Table 3
Overview of the fuel type f specific input parameters for the merit order and its data sources.

Fuel type f	CO_2-intensity ε_f t_{CO_2eq}/MWh	Fuel price c_f €/MWh
oil	0.28 [50]	54.31[a] [51–53]
gas	0.25 [50]	26.10[a,b] [52]
coal	0.34 [50]	14.58[a] [51,52]
lignite	0.36 [50]	6.18[a] [51,52]
nuclear	0.0 [50]	4.18[a] [51]

[a]Year-specific values were used. Here: 2019.
[b]Country-specific values were used. Here: DE.

Table 4
Transmission efficiencies η^{T} used in simulations.
Source: [55].

AT	94.9%	ES	90.8%	HU	88.8%	PL	93.3%
BE	95.1%	FI	96.2%	IE	92.3%	PT	90.6%
CZ	95.1%	FR	93.6%	IT	93.0%	RO	88.4%
DE	96.1%	GB	92.3%	LT	79.5%	RS	84.7%
DK	93.7%	GR	94.2%	NL	95.2%	SI	94.6%

2.6. Fuel type specific emissions and costs

Table 3 shows an overview of the fuel type f specific input parameters used in this study. The fuel type specific cost were used depending on the year and in the case of natural gas, also depending on the country. As fuel type specific CO_2-intensity ε_f, operational net emission factors from [50] were used which, in contrast to life cycle assessment approaches, do not include emissions embodied in infrastructure. This is consistent with the short-term nature of PBDR.

2.7. Transmission efficiency

Based on the methods employed in [33] and [11] we employed a constant transmission efficiency η^{T} to consider all losses for transmission and distribution. Table 4 shows the used average value over the last four published years (2010–2014) for each country [55].

3. Methods

In this study, we propose two approximating methods – the power plant (PP) method and the piecewise linear (PWL) method – to calculate dynamic MEFs and XEFs from the available data. Both methods (PP and PWL) include the application of a country and year specific merit order on historic residual load data to simulate the time-dependent dispatch of conventional power plants and to identify the marginal power plant per time step t. In other words, the prices, XEFs, and MEFs from the simulation depend on the available conventional power plants, the time-dependent RES shares, and the total load, which was proxied by the national total generation.

The PP method takes power plant specific efficiencies as input data while the PWL method approximates these efficiencies internally. More specifically, the PWL method uses national installed generation capacities per fuel type to discretize the fuel type specific generation capacity into virtual power plants. While the PP method may be more precise, the PWL method is more suited for this analysis as power plant specific efficiency data are not readily available for most European countries. However, the PP method is used to validate the PWL method for Germany where more detailed data is available.

Fig. 4 shows a schematic depiction of the data sources and calculation steps. Besides the two main methods (PP and PWL), it also shows the PWL validation mode (PWLv), which is detailed in Section 4.

For the sake of simplicity, from here onwards, the term fuel types also include gas_cc which technically is a special combination of a fuel type and a technology. The remainder of this section describes the calculation of XEFs and MEFs using the PP and the PWL method.

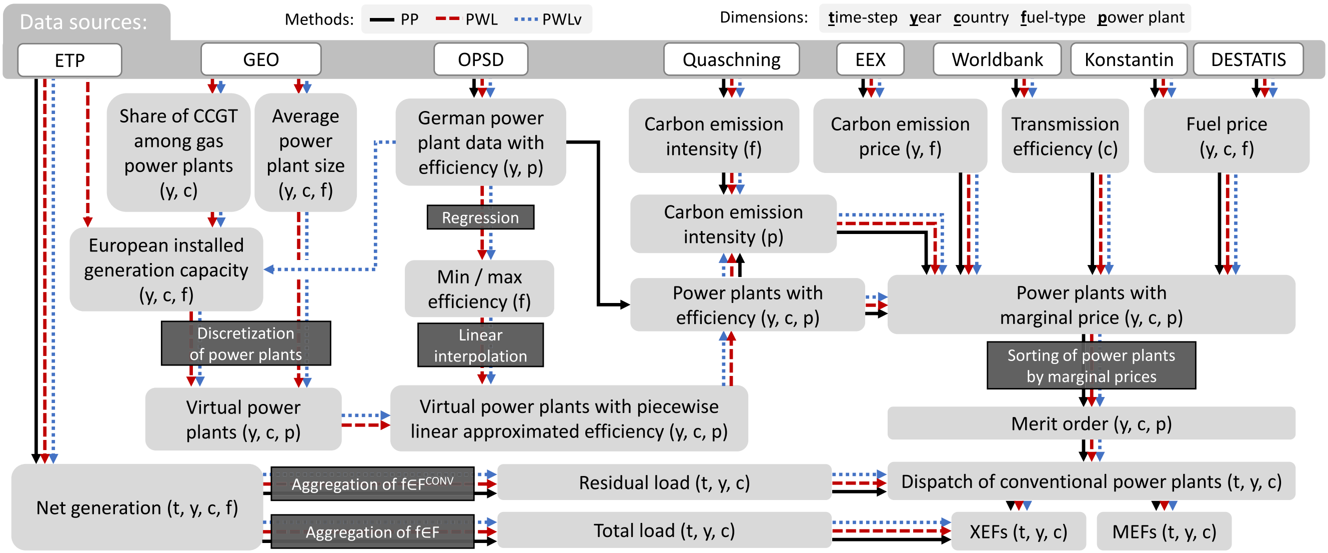

Fig. 4. Schematic depiction of data sources, data subsets and special calculations of the PP, PWL, and PWLv method to calculate CEF. White boxes indicate the following datasets: ETP [28], GEO [47], OPSD [46], Quaschning [50], EEX [49], Worldbank [55], Konstantin [51], DESTATIS [56]. Light gray boxes indicate subsets or modified data. The dimension of each dataset is denoted by the characters t, y, f, and p in brackets. Dark gray boxes indicate special mathematical operations.

3.1. Calculation of MEFs

Regardless of the merit order calculation method, the power plant specific emissions ε_p are given by

$$\varepsilon_p = \frac{\varepsilon_f}{\eta_p^{\mathrm{el}}} \tag{1}$$

where ε_f is the carbon emission intensity per fuel type f and η_p^{el} is the generation efficiency per power plant p.

The time-dependent dispatch is then given by applying the merit order on the residual load. The time-dependent marginal emission factor MEF_t is given by the power plant specific emission intensity ε_p of the marginal power plant in given time step t divided by the transmission efficiency η^{T}:

$$\mathrm{MEF}_t = \frac{\sum_{p\in P} \varepsilon_p \gamma_{t,p}^{\mathrm{m}}}{\eta^{\mathrm{T}}} \tag{2}$$

where $\gamma_{t,p}^{\mathrm{m}}$ is a binary variable:

$$\gamma_{t,p}^{\mathrm{m}} = \begin{cases} 1, & \text{if } \sum_{i=1}^{p-1} P_i^{\mathrm{inst}} < P_t^{\mathrm{resi}} \leq \sum_{i=1}^{p} P_i^{\mathrm{inst}}, \\ 0, & \text{else.} \end{cases} \tag{3}$$

3.2. Calculation of XEFs

In all methods (PP, PWL, PWLv), the grid mix emission factor XEF_t is calculated using the electricity supply specific emissions divided by the electricity consumption:

$$\mathrm{XEF}_t = \frac{\sum_{p\in P} \varepsilon_p \gamma_{t,p}^{\mathrm{x}} P_p^{\mathrm{inst}} \Delta t}{\eta^{\mathrm{T}} \sum_{f\in F} E_{t,f}^{\mathrm{gen}}}. \tag{4}$$

where ε_p is the carbon emission intensity per power plant p, P_p^{inst} is the installed power plant capacity, $\gamma_{t,p}^{\mathrm{x}}$ is the capacity utilization rate defined in Eq. (5), Δt is the time-step-width, η^{T} is the constant transmission efficiency considering all transmission and distribution losses, $E_{t,f}^{\mathrm{gen}}$ is the generated energy per fuel type f and time step t, and F is the set of all generation fuel types.

$$\gamma_{t,p}^{\mathrm{x}} = \begin{cases} 1, & \text{if } \sum_{i=1}^{p} P_i^{\mathrm{inst}} < P_t^{\mathrm{resi}}, \\ 0, & \text{if } \sum_{i=1}^{p-1} P_i^{\mathrm{inst}} \geq P_t^{\mathrm{resi}}, \\ \frac{P_t^{\mathrm{resi}} - \sum_{i=1}^{p-1} P_i^{\mathrm{inst}}}{P_p^{\mathrm{inst}}}, & \text{else.} \end{cases} \tag{5}$$

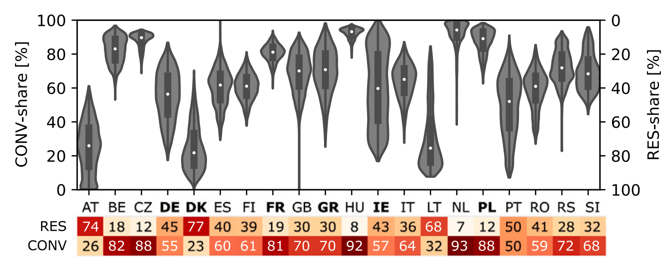

Fig. 5. Top: Distribution of the CONV share (left) and RES share (right) of the total national generation. White dots represent medians. Bottom: Corresponding average values in %.

3.3. Residual load

Since fuel type specific generation data $P_{t,f}^{\mathrm{gen}}$ is available in most European countries, the residual load P_t^{resi} is approximated by the sum of energy generated by the conventional power plants for all methods (PP, PWL, PWLv) and both CEF types (XEF and MEF):

$$P_t^{\mathrm{resi}} = \sum_{f\in F^{\mathrm{CONV}}} P_{t,f}^{\mathrm{gen}} \tag{6}$$

where F^{CONV} is the set of all available conventional fuel types (first 11 fuel types in Fig. 2(a)).

Fig. 5 shows the distributions and average values of the time-dependent CONV share and RES share of the total national generation for the year 2019 for different countries. The average RES share varies from 7% in the Netherlands (NL) to 77% in Denmark (DK). Given Eq. (6) and the limitation to national electricity supply, in this analysis, the CONV share in Fig. 5 is also the residual load share of the total national load.

3.4. Merit order calculation with the PP method

The PP method can be used to calculate the merit order if power plant specific efficiencies are available. The merit order results from sorting all active power plants p according to their ascending marginal

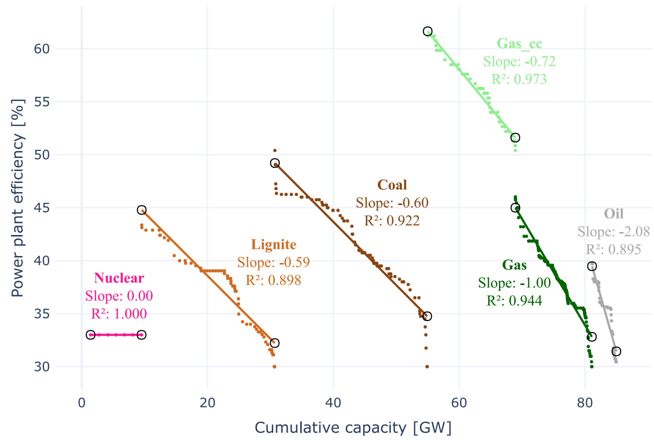

Fig. 6. Ordinary least squares regressions on efficiencies of the power plant list to identify fuel type specific minimal and maximal values (indicated with black open circles). Linear interpolation between these minimal and maximal values result in a piecewise linear function. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Source: Calculations based on [46].

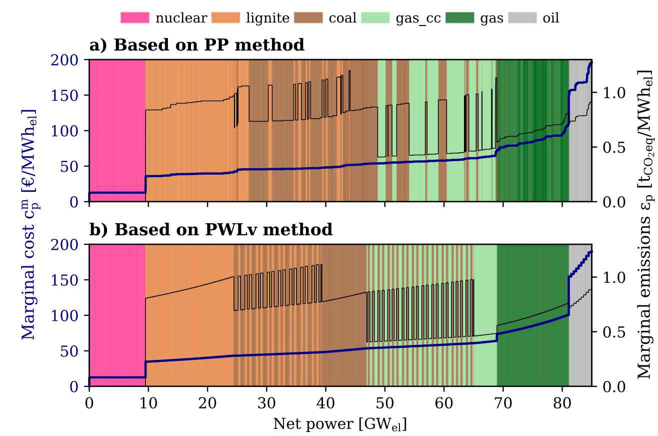

Fig. 7. Merit orders for Germany, 2019 based on (a) PP method and (b) PWLv method, respectively. The background colors correspond to the fuel types. The *x*-axis is shared.

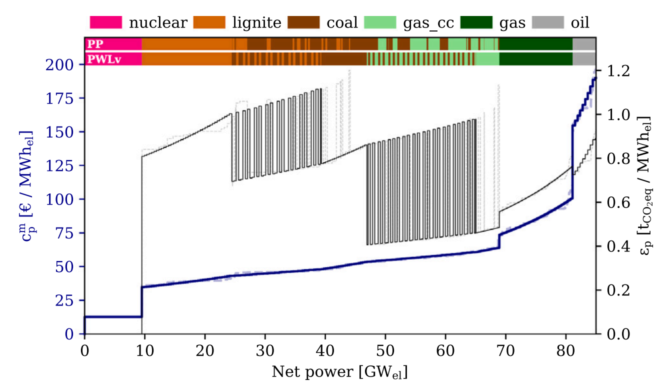

Fig. 8. Direct comparison of PP vs. PWLv method based merit orders. The colors of the additional horizontal bars at the top correspond to the fuel types.

costs c_p^{m}, which are given by:

$$c_p^{\mathrm{m}} = \underbrace{\frac{x_f}{\eta_p^{\mathrm{el}}}}_{\text{fuel costs}} + \underbrace{\frac{\varepsilon_f}{\eta_p^{\mathrm{el}}} c^{\mathrm{GHG}}}_{\text{carbon-related costs}} \tag{7}$$

where η_p^{el} is the efficiency per power plant p (data from Section 2.3), c^{GHG} is the carbon emission price (data from Section 2.5), and ε_f and x_f are the fuel type specific emission intensities and prices, respectively (data from Section 2.6).

Fig. 7a) exemplarily shows the resulting merit order with power plant specific marginal costs c_p^{m} and emissions $\varepsilon_p^{\mathrm{m}}$ for Germany, 2019.

3.5. Merit order calculation with the PWL method

The PWL method is a piecewise-linear approximation approach that can be used to approximate the country and year specific merit order if power plant specific capacity and efficiency data are unavailable. For most European countries only fuel type specific data are provided, hence the PP method which is based on the power plant list including power plant efficiencies is not applicable in these countries. A very simple approach to approximate MEFs is the usage of fuel type specific efficiencies. In this PWL method, instead, we assume that all countries have the same maximum and minimum efficiency per fuel type and that within each fuel type the capacity over the range of occurring efficiencies is uniformly distributed. These assumptions allow us to approximate the efficiencies of the power plants by a piecewise-linear function. For each fuel type, the minimum and maximum efficiencies were determined by the minimum and maximum values of an ordinary least squares regression of the power plant efficiencies of the German power plant list, see Fig. 6. To enable the non-disjunct structure of the merit order, which can be observed in reality, the total generation capacities per fuel type were discretized into discrete equally sized virtual power plants. In our case, country and fuel type specific values were used, see Supplementary Material D. They were computed from the GEO power plant list [47], which contains capacity data but no efficiency data.

3.6. Limitations

The resulting MEFs depend on the determination of marginal power plants, which is subject to some uncertainty since the merit order is calculated based on an approximation of marginal costs and installed generation capacity. Therefore, the error generated through the improper calculation of the merit order has a substantially stronger effect on MEFs than on XEFs.

As did all previous studies presented in Table 1, we do not consider transnational power flows in the calculation of MEFs since there is no existing method to do so. Commercial entities like Tomorrow [27,57] provide estimated MEFs considering cross border flows, however their method is not published.

Due to these two limitations, the MEFs calculated in this study are subject to an unquantified level of uncertainty. However, the authors deem this to be reasonably low due to the high number of empirically derived parameters factored into this study.

4. Validation of the PWL method

To evaluate the approximation error of the PWL method, the PP method was applied to the detailed dataset for Germany described in Section 2.3 for the years 2015–2019. For this, we introduce the PWLv method as a validation variant of the PWL method which ensures consistency of data sources between the two main methods (PP and PWL). In Fig. 4, it can be seen that in contrast to the PWL method, the PWLv method used installed generation capacity data from the German OPSD power plant list to ensure the same data basis with the PP method. The PWLv-based merit order for Germany, 2019 is shown in Fig. 7(b); and for better comparison, Fig. 8 shows the same merit order together with the PP-based merit order. Fig. 9 shows a comparison of the two CEF-types and the two calculation methods applied to Germany

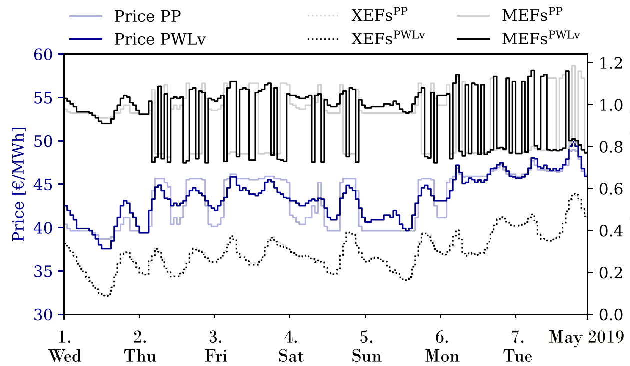

Fig. 9. Comparison between XEFs, MEFs, and marginal prices for the methods PP and PWLv in hourly resolution for the first week in May 2019 in Germany.

	type 1		type 2			type 3		
	$\delta^{MO,c}$	$\delta^{MO,\varepsilon}$	δ^{P}	δ^{MEF}	δ^{XEF}	$\delta^{\overline{P}}$	$\delta^{\overline{MEF}}$	$\delta^{\overline{XEF}}$
2015	1.78	5.63	2.40	9.91	1.21	2.11	1.79	1.16
2016	1.52	4.93	1.67	9.64	0.73	0.79	0.40	0.46
2017	1.51	7.48	1.93	6.38	0.53	0.06	0.04	0.47
2018	1.54	14.26	1.87	9.68	0.65	0.04	1.11	0.64
2019	1.36	16.65	1.82	16.21	1.14	0.06	0.42	0.43
mean	1.54	9.79	1.94	10.36	0.85	0.61	0.75	0.63

Fig. 10. Relative approximation errors of the PWL method vs. PP method for Germany and the years 2015–2019 in % grouped in three error types.

	AT	BE	CZ	**DE**	**DK**	ES	FI	**FR**	GB	**GR**	HU	**IE**	IT	LT	NL	**PL**	PT	RO	RS	SI
2015	4	5	6	28	4	10	4	5	5	4	5	4	4	2	4	20	3	9	1	3
2016	4	5	8	24	4	8	4	5	5	3	5	4	4	2	4	16	3	7	1	3
2017	4	9	4	28	4	25	4	11	35	3	5	6	29	2	10	4	9	14	2	4
2018	8	7	6	68	4	33	6	13	31	3	5	6	23	1	11	26	8	12	2	4
2019	8	7	12	84	12	19	6	13	23	3	5	8	12	1	12	42	7	11	2	4

Fig. 11. Number of fuel type changes along PWL-based merit orders for the years 2015–2019.

for the first week in May 2019. It can be seen that the PWL method succeeds to represent the MEFs well. A whole-year comparison between the resulting MEF_t^{PP} and MEF_t^{PWLv} can be found in Supplementary Material G.

Fig. 10 shows the values of the three different relative error types that were calculated to evaluate the approximation quality of the PWL method compared to the PP method:

1. The error of power plant specific marginal costs c_p^m and emission intensities ε_p along the merit order ($\delta^{MO,c}$, $\delta^{MO,\varepsilon}$). $\delta^{MO,c}$ and $\delta^{MO,\varepsilon}$ were calculated as averaged relative errors of marginal costs and emission intensities, respectively, between the PWLv method and the PP method along the merit order. To be able to deal with the different cumulative power values in the merit orders, the merit order was discretized by 10 MW-elements which are more than ten times smaller than the average power plant.
2. The error of time-dependent prices, MEFs, and XEFs (δ^{P}, δ^{MEF}, δ^{XEF}).
3. The error of yearly aggregated prices, MEFs, and XEFs ($\delta^{\overline{P}}$, $\delta^{\overline{MEF}}$, $\delta^{\overline{XEF}}$).

From Fig. 10, one can see that while all other error types are below 2.5%, $\delta^{MO,\varepsilon}$ and δ^{MEF} are above. However, due to the high number of lignite and coal power plants with similar marginal costs, Germany has by far the most fuel type changes along the merit order, see Fig. 11. And since $\delta^{MO,\varepsilon}$ and δ^{MEF} correlate with the number of fuel type changes, they are expected to be smaller for all other countries.[2]

5. Analyses and discussions for European countries

In the following analysis, we apply the previously developed methods (PP and PWL) presented in Section 3 to data described in Section 2, see also Fig. 4. More specifically, we apply the PP method to the German power plant list described in Section 2.3 and the PWL method to data from 20 European countries described in Section 2.2. The remaining European countries were removed from the analysis due to poor data quality or insufficient electricity demand (small countries). The rejection criteria are detailed in Supplementary Material F.

5.1. Merit orders and CEFs for European countries

Fig. 13 shows the distribution of the residual load (the load that has to be provided by conventional power plants) from the analyzed countries described in Section 3.3. The median value for France (FR), 47.31 GW, is 739 times greater than that of Lithuania (LT), 0.06 GW. The respective maximum values are 69.67 GW and 0.80 GW. Detailed depictions of the resulting merit orders for the years 2017–2019 for the 20 analyzed countries are contained in Supplementary Material H.

In Fig. 12, the distributions of XEFs, MEFs, and marginal prices resulting from the simulations are depicted. One can see that the MEFs tend to be higher than the XEFs. Only in the Netherlands (NL) is the median of XEFs higher than the median of MEFs. The reasons are a RES share of only 7%, a coal baseload mostly, and efficient gas_cc marginal power plants. However, the average values of MEFs are higher than those of XEFs for all countries. This means that the marginal power plant, on average, emits more emissions per unit of electricity than the national generation mix. From Fig. 12, we can divide the 20 countries into three groups. The first group contains Poland (PL) and France (FR), where fluctuations of the CEFs are low compared to the other countries and the medians are almost identical. The reason for this could be that the main marginal power plant's fuel type is also the main energy source, e.g., coal for PL, nuclear for FR. The second group includes Austria (AT) and Czech Republic (CZ), where the value sets of XEFs and MEFs are disjointed due to dominant low carbon energy sources, such as hydro in Austria with 26% of generation, or nuclear and solar in Czechia (CZ) with 10.4% and 9.8% generation, respectively. All other countries are in the third group, where the value sets of XEFs and MEFs intersect, but the medians differ substantially. An explanation could be that the marginal power plant's fuel type is only one of many energy sources, including RES.

5.2. Correlation analysis of emissions and prices

For the correlation analysis of the CEFs, we follow [24] in using the Spearman rank correlation coefficient r as the relationship between CEFs and marginal costs is not expected to be linear [24]. This coefficient r quantifies how well the relationship between two variables can be described using a monotonic function. In the Supplementary Material I, the correlation between electricity prices (simulated and historic) and the calculated CEFs ($XEFs^{PP}$, $XEFs^{PWLv}$, $MEFs^{PP}$, $MEFs^{PWLv}$) for Germany for the years 2017–2019 are presented in scatter plots. It can be seen that the XEFs correlate positively with the simulated and the historic prices for all three years 2017–2019 and for the methods PP and PWLv (r-values range between 0.62 and 0.88). In contrast, the MEFs have negative r-values (between −0.16 and −0.42) for all mentioned combinations, which is a first indicator of the phenomenon where PBDR leads to a carbon emission increase. Fig. 14 shows r-values for all analyzed countries using the PWL method. The correlation values are positive for 16 and negative for 4 of the 20 countries.

[2] The Pearson correlation coefficients for $\delta^{MO,\varepsilon}$ and δ^{MEF} are 0.99 and 0.77, respectively.

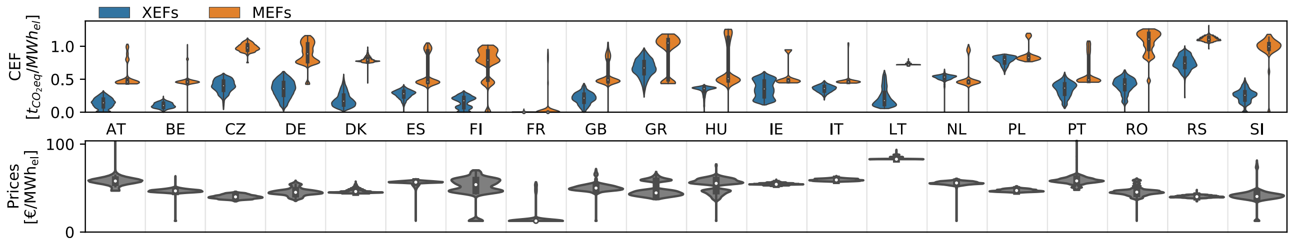

Fig. 12. Distribution of resulting CEFs and marginal prices for 2019. Note that 1.2% of AT's values (104–190 €/MWh$_{el}$) were trimmed.

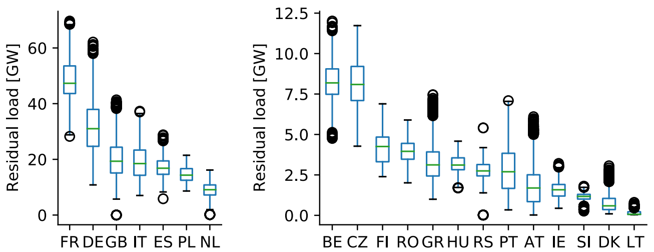

Fig. 13. Distribution of residual loads for countries under study in descending order of median. Plots were splitted to enhance readability.

	AT	BE	CZ	**DE**	**DK**	ES	FI	**FR**	GB	**GR**	HU	**IE**	IT	LT	NL	**PL**	PT	RO	RS	SI
XEFs	0.92	0.98	0.98	0.88	0.67	0.78	0.98	1.00	0.96	0.40	0.88	0.77	0.30	0.74	-0.00	0.41	0.61	0.84	0.35	0.89
MEFs	0.31	0.97	0.93	-0.18	0.99	-0.05	0.24	1.00	0.47	-0.14	-0.37	0.57	0.93	1.00	0.70	0.57	0.20	-0.01	1.00	0.86

Fig. 14. Spearman correlation coefficients *r* between CEFs (MEFs, XEFs) and marginal prices with the PWL method for the year 2019.

	AT	BE	CZ	**DE**	**DK**	ES	FI	**FR**	GB	**GR**	HU	**IE**	IT	LT	NL	**PL**	PT	RO	RS	SI
ΔC	-24	-6	-6	-12	-6	-4	-10	-21	-16	-24	-13	-4	-4	-3	-5	-5	-14	-11	-3	-19
ΔXE	-53	-45	-21	-37	-38	-10	-10	-92	-57	-3	-13	-30	-3	-53	-1	-7	-20	-20	3	-27
ΔME	11	-7	-5	10	-5	25	-4	-64	-3	53	31	3	-4	-3	-5	-1	22	4	-3	-13

Fig. 15. Relative annual changes of cost and carbon emissions resulting from load shift simulation for 2019 in %. The grid mix emissions are based on $\mathrm{XEF}_t^{\mathrm{PWL}}$, the marginal carbon emissions are based on $\mathrm{MEF}_t^{\mathrm{PWL}}$.

5.3. Price-based load shift analysis

For environmental evaluation of PBDR, only the source and sink hours are relevant, i.e., the hours where energy is shifted from and to. The analysis of the emissions without the consideration of the electricity price, which is the driving signal for PBDR, might be misleading. Thus, we quantify and compare the incentives and effects of PBDR for the years 2017–2019 and the 20 analyzed countries with a simulated load shift: Every day, an hourly load of 1 kWh is shifted from the most expensive to the cheapest hour of that day. Annual simulations were conducted for the years 2017–2019 for the 20 analyzed countries. The electricity prices relate to the marginal costs of the previous simulation.

Since MEFs quantify the marginal system effects, the ME changes are the total emission changes, i.e., if MEs increase by 1 t, total emissions increase by 1 t, too. In the remainder of the paper, we refer to the total emission changes as ME changes only to distinguish them from XE changes, which are the change in emissions calculated from the XEF.

In Fig. 15, the relative changes of cost and carbon emissions of the shifted energy due to load shifts are shown. Since we consider PBDR, the cost reductions are the incentives and the changes in carbon emissions are the effects. It can be seen that, in contrast to the costs, which decreased for all countries as expected, the carbon emissions increased for some countries. MEs increased for the eight countries Austria (AT), Germany (DE), Spain (ES), Greece (GR), Hungary (HU), Ireland (IE), Portugal (PT), and Romania (RO).

XEs are usually reduced since PBDR leads to load shifts from high-XEF-hours to low-XEF-hours. The only exception of the 20 countries is Serbia (RS), where the load shifts increased the total XEs by 3%. The reason might stem from the fact that Serbia's power supply system is dominated by hydro (run-of-river and pondage) and lignite. In the simulation, the marginal power plant for Serbia is always a lignite power plant (see also Fig. 18 and the merit order in Supplementary Material H). With the aid of the pondage, hydro power plants have storage capacities enabling them to shift electricity generation from low-load-hours (0:00–6:00) to peak load hours (8:00, 19:00), see Fig. 16. While this also happens in other countries, in Serbia the pondage effect has more weight as there are no significant shares of vRES such as wind or solar. A similar case, where PBDR led to an increase in XEs is reported by [34] for Norway in the year 2015.

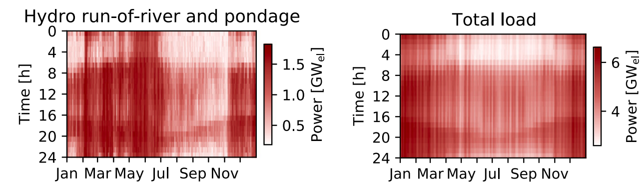

Fig. 16. Historic data for the year 2019 for Serbia: Hydro run-of-river and pondage (left) and total load (right).
Source: [28].

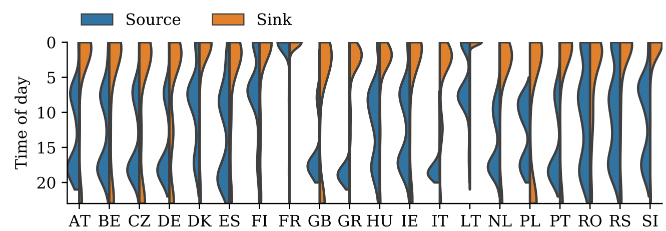

Fig. 17. Distribution of source time and sink time of simulated load shifts for 2019.

Fig. 17 shows the source and sink time of the load shifts. These are the times with the highest and lowest prices of the day. For most countries, the distribution of source time has two humps: One for 5:00–10:00 and another for 16:00–20:00. This result was expected by the authors since it reflects the double-hump pattern of historic price curves. The load shift sink is mainly at night (21:00–07:00). Only in Germany and Italy does the sink occasionally occur around midday (11:00–15:00). In France, source and sink hours are both just after midnight. This is because France's sole conventional energy source is usually nuclear which is evaluated with a constant efficiency by the data source [46]. Therefore, the daily price spreads were zero on most days, and load shifts were only carried out in cold winter months where coal and gas_cc power plants additionally stepped in to cover the increased load.

Fig. 18 gives insights on the marginal fuel type combination of the conducted load shifts. For the small country of Lithuania (LT), it can be seen that the national energy supply with gas as the only energy source and a low ratio between load and average power plant size provides only little incentive for load shifting.

	AT	BE	CZ	**DE**	**DK**	ES	FI	**FR**	GB	**GR**	HU	**IE**	IT	LT	NL	**PL**	PT	RO	RS	SI
oil⇒gas_cc	28	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
oil⇒coal	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
nuclear⇒nuclear	-	1	-	-	-	-	8	320	-	-	-	-	-	-	-	-	-	-	-	-
lignite⇒nuclear	-	-	-	-	-	-	-	-	-	-	4	-	-	-	-	-	-	5	-	31
lignite⇒lignite	-	-	354	86	-	-	-	-	-	119	75	-	-	-	-	7	-	171	365	300
lignite⇒coal	-	-	-	14	-	-	-	-	-	-	-	-	-	-	-	35	-	21	-	-
gas⇒lignite	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	34
gas⇒gas_cc	2	1	-	-	-	-	-	-	33	-	8	-	-	-	-	-	18	-	-	-
gas⇒gas	-	-	-	-	-	-	-	-	-	-	-	-	-	365	-	-	-	-	-	-
gas⇒coal	-	-	-	-	-	-	-	-	13	-	-	-	-	-	-	-	3	-	-	-
gas_cc⇒nuclear	-	6	-	-	-	1	-	9	9	-	-	-	-	-	2	-	-	-	-	-
gas_cc⇒lignite	-	-	-	22	-	-	-	-	-	241	129	-	-	-	-	-	-	20	-	-
gas_cc⇒gas_cc	179	330	-	1	-	139	43	-	108	5	149	266	345	-	259	-	167	1	-	-
gas_cc⇒coal	130	12	-	22	3	144	51	11	114	-	-	63	10	-	45	-	150	9	-	-
coal⇒nuclear	-	-	-	-	-	-	32	22	5	-	-	-	-	-	-	-	-	-	-	-
coal⇒lignite	-	-	11	148	-	-	-	-	-	-	-	-	-	-	-	77	-	112	-	-
coal⇒gas_cc	9	15	-	-	-	25	6	-	44	-	-	36	9	-	47	-	8	1	-	-
coal⇒coal	16	-	-	72	362	56	225	3	39	-	-	-	1	-	12	246	19	25	-	-

Fig. 18. Frequency of load shift events per country and marginal fuel type combination (denoted in the form $f^{\text{source}} \Rightarrow f^{\text{sink}}$) for the year 2019.

	AT	BE	CZ	**DE**	**DK**	ES	FI	**FR**	GB	**GR**	HU	**IE**	IT	LT	NL	**PL**	PT	RO	RS	SI
•ΔC	-24	-6	-6	-12	-6	-4	-10	-21	-16	-24	-13	-4	-4	-3	-5	-5	-14	-11	-3	-19
ΔXE	-53	-45	-21	-37	-38	-10	-10	-92	-57	-3	-13	-30	-3	-53	-1	-7	-20	-20	3	-27
ΔME	11	-7	-5	10	-5	25	-4	-64	-3	53	31	3	-4	-3	-5	-1	22	4	-3	-13
ΔC	-20	-6	-6	-10	-5	-3	-8	-21	-15	-3	-11	-2	0	-3	-0	-4	-5	-5	0	-15
•ΔXE	-57	-48	-24	-44	-59	-23	-20	-93	-59	-35	-17	-42	-26	-70	-10	-11	-38	-25	-22	-38
ΔME	14	-7	-5	6	-4	20	-8	-64	-4	-8	30	-4	3	-3	-1	1	16	3	0	-12
ΔC	-12	-5	-5	-3	-5	-2	-8	-19	-12	10	-2	-2	-3	-3	-3	-3	-5	-0	-3	-8
ΔXE	-30	-37	-19	-15	-37	-3	-8	-63	-48	-6	-6	-18	-1	-53	-1	-4	-8	-4	3	-24
•ΔME	-51	-30	-9	-38	-7	-50	-27	-84	-53	-47	-36	-47	-43	-3	-47	-32	-54	-28	-3	-21

Fig. 19. Relative annual changes of Cost (C), Grid Mix Emissions (XE), and Marginal Emissions (ME) resulting from load shift simulations for 2019 in % with "•" indicating the optimized criteria. The XEs are based on $\mathrm{XEF}_t^{\mathrm{PWL}}$, the MEs are based on $\mathrm{MEF}_t^{\mathrm{PWL}}$.

5.4. CEF-based load shift analysis

For PBDR, the time-dependent electricity price is the incentive signal that determines the source and sink hours. However, conducting DR based on XEFs or MEFs could be an option for consumers who want to minimize their carbon emissions. In this analysis, we rerun the previous load shift simulation with XEFs or MEFs as incentive signals, so 1 kWh is shifted every day from the hour with the highest XEF or MEF of that day to the lowest, respectively. In Fig. 19, the relative changes of cost and carbon emissions of the shifted energy due to load shifts are shown; note that the results from Section 5.3 are repeated for better comparison. The resulting effects of the XEF-based load shifts are similar to that of the cost-based load shifts: Both lead to increased MEs in 8 countries. In contrast, the MEF-based load shifts lead to ME savings between 3 and 84% with an average of 35%, albeit reducing the average cost-saving potential by 56% compared to cost-based load shift.

5.5. Detailed discussion of six sample countries

In the following, the reasons and conditions under which PBDR lead to increased carbon emissions will be discussed using detailed results of the load shift analyses of six exemplary countries for the year 2019, shown in Fig. 20. For corresponding analyses of the remaining 14 countries, see Supplementary Material K. The six countries were selected because first, they are representative in terms of country size and the range of relative annual changes from Fig. 15, including its maximum (GR) and minimum (FR) of ME changes, and second, they have different interesting attributes, e.g., the dominance of nuclear (FR), high wind share (DK), the dominance of lignite/coal (PL), or being a small country very reliant on wind and gas_cc (IE). For each country, Fig. 20 shows (a) the merit order, (b) the histogram of P_t^{resi} as the range of possible load shifts, (c) the load shifts with its sources and sinks, and (d) their inverted load duration curves. For according plots for all 20 countries for the years 2017–2019, see Supplementary Material J. In Fig. 20, the three countries in the first row (DE, GR, IE) have increased MEs in Fig. 15, the countries in the second row (DK, FR, PL) do not. (To guide the reader's eye, the six sample countries have been marked with bold letters for several previous diagrams.)

Germany (DE). Even though Germany has a comparatively diversified energy supply, the main marginal fuel types are lignite, coal, and gas_cc, which are also the main causers of the merit order dilemma of emissions. The results show 159 load shifts in which the marginal fuel type does not change. In these cases, the load is generated by a generation unit with the same fuel type but with a higher efficiency, which leads to reductions in cost and MEs. With 192 cases, more than half of the German load shifts display a reduction in MEs (148 coal-to-lignite, 22 gas_cc-to-coal, and 22 gas_cc-to-lignite). Only 14 energy units were shifted towards a situation with a greener marginal fuel type (lignite-to-coal).

Greece (GR). In Greece, the increase of MEs due to load shifting is particularly strong with 53%. The reason is that the residual load oscillates most days around the capacity limit between lignite and gas_cc at around 4 GW leading to 241 gas_cc-to-lignite load shifts, which are the most disadvantageous occurring load shifts regarding the unwanted effect of increasing MEs. Due to Greece's still moderately developed expansion of renewable energies with 30% RES share, the potential for reducing XEs is only 3%.

Ireland (IE). With a wind share of 40%, Ireland's RES share of 43% is similar to that of Germany even though there is very little solar power. This drives the XE saving to up to 30%. However, ME changes are slightly positive with 3% due to 63 gas_cc-to-coal load shifts. Only the 36 coal-to-gas_cc-load shifts imply changing to a greener marginal fuel type while the vast majority of load shifts (266) stay within the dominant fuel type gas_cc.

Denmark (DK). In Denmark, the load shifts lead to 40% XE reductions. This is mainly caused by the high RES share of 76% of which wind_onshore contributes almost half. The national residual load P_t^{resi} is subject to strong seasonal fluctuations. Causing factors could be power demand for heating during winter and reduced imports of German excess solar power. The MEs are moderately reduced by 6%. More than 99% of the load shifts are within the fuel type of coal, thus, yield only emission reductions through higher power plant efficiencies.

France (FR). In France, 71% of electricity is produced by nuclear power plants making the country's national power supply system heavily conventional-based, yet low in carbon emissions. The national power supply gives only little economic incentive for load shifting since the residual load is predominantly in the range of marginal nuclear power. Only in the cold winter months, when the residual load exceeds the nuclear power capacity limits, incentives for intraday load shifting are created. There are 31 load shifts into hours with nuclear as marginal fuel type: 9 shifted from gas_cc and 22 from coal. These few cases do not lead to particularly high CO_2 savings in absolute terms. In relative terms, however, due to the low emission baseline level of France's power system, they contribute to the highest savings of all analyzed countries: 92% XE and 64% ME savings.

Poland (PL). Poland has a low RES share. Predominant fuel types are coal (52%) and lignite (26%). In the merit order, they are intertwined due to similar marginal cost levels — in contrast to Greece where the fuel types lignite and gas_cc form continuous blocks in the merit order. This leads to all combinations of load shifts between the two fuel types: 35 lignite-to-coal-shifts, 77 coal-to-lignite-shifts, 7 lignite-to-lignite-shifts, and 246 coal-to-coal-shifts. Together these result in 7% ME savings mainly stemming from power plant efficiency gains of the coal-to-coal load shifts.

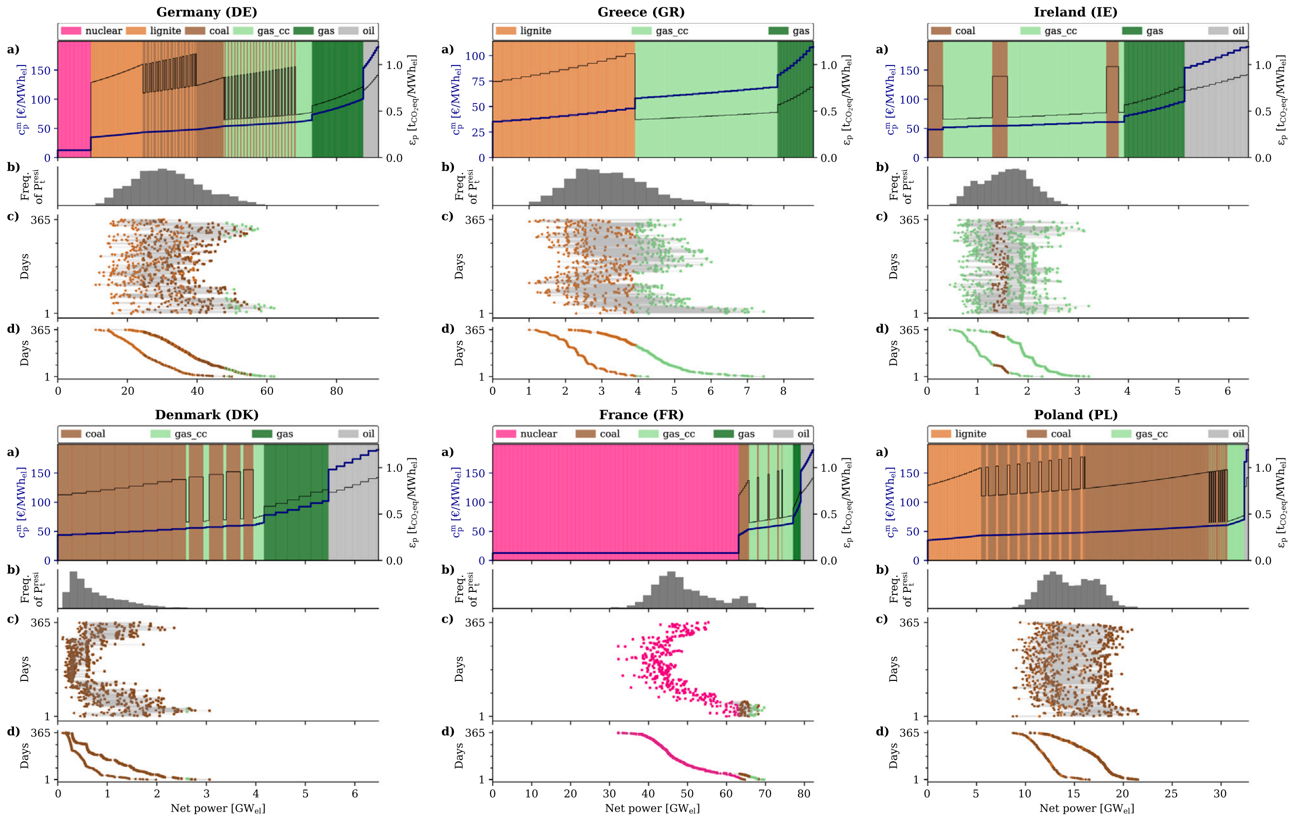

Fig. 20. Load shift analyses of 6 European countries for the year 2019 based on the PWL method: **(a)** Merit order with marginal costs c_p^m (left) and emission intensities ε_p (right), **(b)** histogram of residual load P_t^{resi}, **(c)** load shifts of all days of the year (squares indicating sources and triangles indicating sinks), and **(d)** inverted load duration curves of sources (right) and sinks (left)). The x-axis (net generation power in GW$_{el}$) is shared across the four subplots.

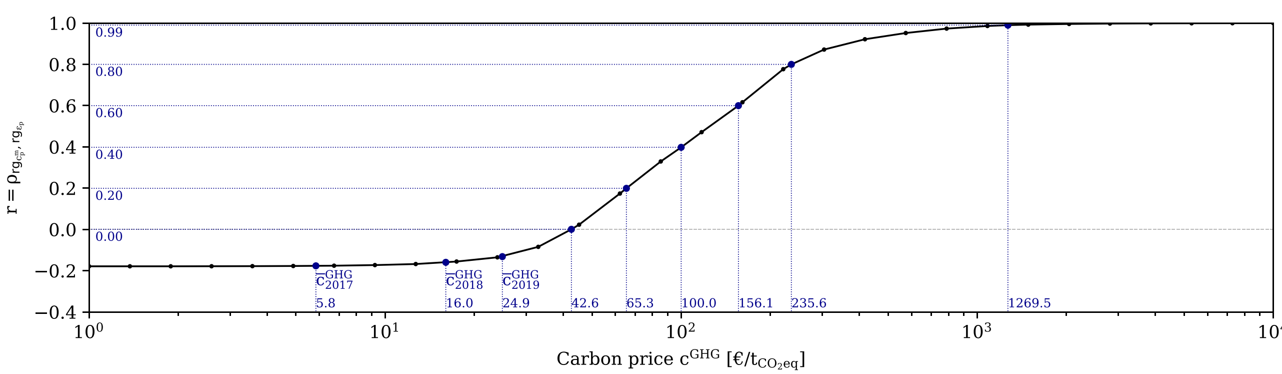

Fig. 21. Sensitivity analysis of the carbon price c^{GHG} and the Spearman correlation coefficient r between marginal costs c_p^m and marginal emissions ε_p^m with German power plant data in 2019. Indicated in blue color, the average carbon prices $\bar{c}_*^{GHG}$ for the years 2017–2019 and additional interesting carbon prices and r-values are added. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5.6. Impact of carbon price

A promising measure to solve the merit order emission dilemma is to set a price for carbon emissions in the form of a carbon price or carbon tax to an appropriate level. This increases the correlation between marginal costs and carbon intensities in the merit order.

5.6.1. Impact on marginal costs–emissions correlation

To demonstrate this, a sensitivity analysis was carried out in which the merit order of the German power plants for the year 2019 was determined for different hypothetical carbon prices. To quantify the effect on the merit order, the Spearman correlation coefficient r between the marginal prices c_p^m and the power plant specific carbon intensities ε_p along the merit order was calculated for each scenario. The quantitative results can be seen in Fig. 21. It shows negative r values for carbon prices below 42.58 €/t. For comparison, the average carbon prices for the years 2017–2019, $\bar{c}_{2017}^{GHG}$, $\bar{c}_{2018}^{GHG}$, and $\bar{c}_{2019}^{GHG}$, were 5.8 €/t, 16.0 €/t and 24.9 €/t, respectively. $r = 0$ means that CEFs and marginal costs are decoupled. $r = 0.2$ was calculated for $c^{GHG} = 65.3$ €/t, $r = 0.4$ for $c^{GHG} = 100.0$ €/t, $r = 0.6$ for $c^{GHG} = 156.1$ €/t, and $r = 0.8$ for $c^{GHG} = 235.6$ €/t. In comparison, the German Federal Environment Agency suggests the usage of climate damage costs of 180 €$_{2016}$/t for the year 2016, 205 €$_{2016}$/t for 2030, and 240 €$_{2016}$/t for 2050 [58]. For $r \gtrapprox 0.8$ or $c^{GHG} \gtrapprox 235.6$ €/t, the marginal gains of r decrease. In order to reach $r = 0.99$, a carbon price of 1269.5 €/t is needed.

5.6.2. Impact on the merit order

Fig. 22 shows the corresponding effects on the merit order. One can see that with increasing carbon prices, the low-emission gas_cc power

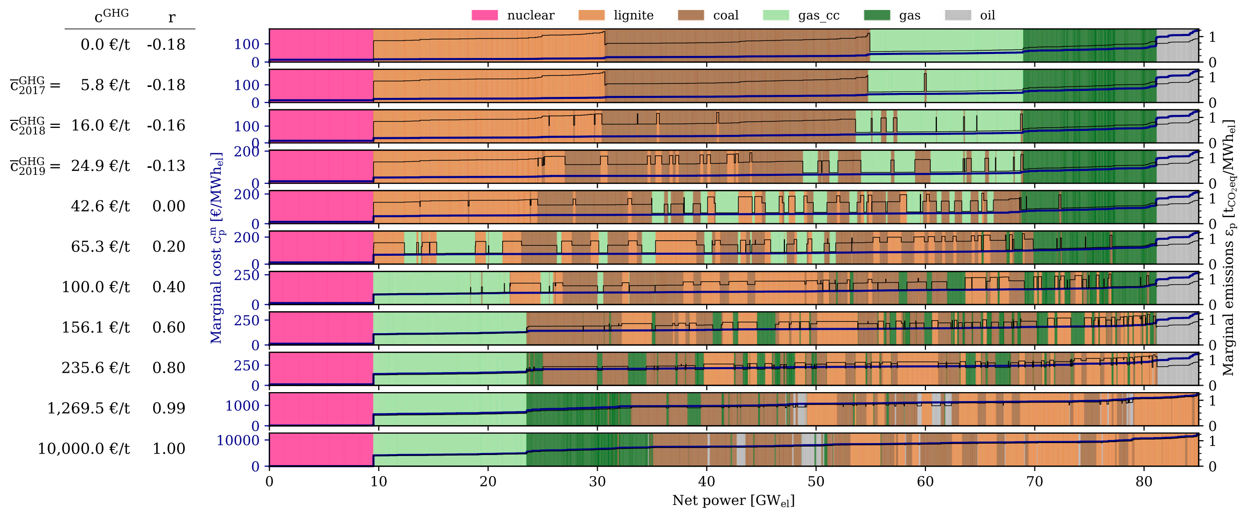

Fig. 22. How the German merit order in 2019 and its Spearman correlation coefficient r between marginal costs c_p^m and marginal emissions ε_p^m would change with carbon price c^{GHG}. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

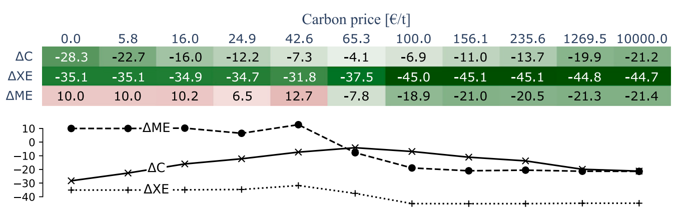

Fig. 23. Relative annual changes of Cost (C), Grid Mix Emissions (XE), and Marginal Emissions (ME) resulting from load shift simulation for 2019 in % for different carbon prices. The grid mix emissions are based on XEF_t^{PP}, the marginal carbon emissions are based on MEF_t^{PP}.

plants gain a comparative economic advantage over lignite and coal and shift to the left side of the merit order. With $c^{GHG} = 100$ €/t, almost all gas_cc power plants are directly behind nuclear. The same happens to the gas power plants, coal power plants, and for c^{GHG} somewhere above 236 €/t even to oil power plants. These values mostly align with the simulation results in [59]. For $c^{GHG} = 10\,000$ €/t, where r reaches the value 1.00, the carbon emission intensity ε_p (black line) is, except for a few small power plants, monotonically increasing and fully correlated with the marginal price c_p^m (blue line).

5.6.3. Impact on load shifting

In a final analysis, we calculated the load shift effects on MEs, XEs, and costs for different carbon prices for the case of Germany in 2019. The results are depicted in Fig. 23.

In general, an increasing carbon price leads to decreasing MEs and XEs. However, in the special cases of carbon price raise from 24.9 €/t to 42.6 €/t and from 156.1 €/t to 235.6 €/t, an increase of MEs and XEs can be observed. This is because with $c^{GHG} = 42.6$ €/t, gas_cc power plants move into the 35 GW area, around where the residual load fluctuates (see Fig. 20b for Germany) increasing the number of gas_cc-to-lignite and gas_cc-to-coal load shifts, see Fig. S21 in Supplementary Material J. At $c^{GHG} = 65.3$ €/t, gas_cc power plants already arrived on the lower half of the residual load range and therefore act more frequently as load shift sink. $c^{GHG} = 65.3$ €/t is already sufficient to achieve 58% of the possible achievable ME savings, and $c^{GHG} = 100.0$ €/t yields 93% of the possible achievable ME reduction of 21.4%.

The effects on XEs are similar to the effects on MEs. Increasing emissions for increasing carbon prices can be observed for the same price steps and traced back to the same reasons, but with lower amplitude, due to the damping influence of averaging.

The effect curve on costs in Fig. 23 is concave. For $c^{GHG} \leq 65.3$ €/t, the cost savings decrease with increasing carbon prices. The reducing daily price spreads are caused by the convergence of marginal costs of power plants in the relevant residual load range (around 35 GW) as the high carbon intensities of formerly cheap coal and lignite power plants are effectively penalized by the increasing carbon price. For $c^{GHG} > 65.3$ €/t, the carbon-related marginal costs (cf. Eq. (7)) increasingly outweighs the fuel costs and ultimately makes the fuel costs insignificant. Through the formation of coherent technology blocks – now in the new ascending order of carbon intensity – steps in the marginal costs curve are shaped (e.g., at 23 GW) which in turn lead to higher price spreads.

5.7. Discussion summary

While MEFs are essential for quantifying the carbon differential of load shifts, XEFs are more suitable for calculating the carbon emissions of a static electricity load profile. Also, XEFs can be determined with less uncertainty and in a straightforward approach, which is reflected in their high availability.

European national electricity supply systems differ widely in both size (0.13–49 GW residual load) and composition (7%–77% RES share), which is reflected in the varying prices and CEFs that resulted from the simulation, Fig. 12. The differences between the European countries became even clearer when running yearly simulations of daily load shifts on the basis of the calculated prices and CEFs. The electricity cost-saving potentials ranged between 3% for Lithuania (LT) and Serbia (RS) and 24% for Austria (AT) and Greece (GR). The resulting changes in MEs varied between 64% decrease for France (FR) and 53% increase for Greece (GR), with increases in eight countries (AT, DE, ES, GR, HU, IE, PT, RO). The changes of XEs varied between −92% for France (FR) and +3% for Serbia (RS), with Serbia being the only country where XEs increase. Averaged over all countries, the costs decreased by 10.4%, the XEs decreased by 26.9%, but the MEs increased by 2.1%. While XEF-based load shifts, like the price-based load shifts, led to ME increases in eight countries, MEF-based load shifts resulted in average emission savings of 35%, albeit with 56% lower cost savings. A final sensitivity analysis regarding the carbon price brought the following salient findings: (1) For Germany, a carbon price of 42.6 €/t was necessary to decouple emissions from prices, i.e., where r, the Spearman correlation coefficient of emissions and prices along the merit order, is zero. (2) A carbon price increase from 0 to 156.1 €/t led to a switch between gas_cc and lignite/coal in the German merit order and flipped effects of the according price-based load shifts on carbon emissions from a 10% increase to a 21% decrease. (3) Increases of the carbon price beyond 156.1 €/t led to insignificant changes.

6. Conclusions

The aim of this paper was the quantification and discussion of the effects of PBDR on operational carbon emissions for European countries. Straightforward approaches based on the calculation of XEFs are not suitable for this purpose due to the characteristics of electricity markets. More adequate methods based on the knowledge of marginal power plants require detailed data, thus MEF values are not readily available for European countries. In this paper, we therefore proposed a method (PWL) to approximate MEFs with readily available datasets and validated it with another method (PP) using power plant specific efficiency data from Germany. We then applied the PWL method to 20 European countries for the years 2017–2019 to calculate prices, MEFs, and, for comparison purposes, XEFs. The resulting prices and CEFs served as basis for subsequently conducted load shift simulations, to evaluate its effects on carbon emissions. Starting from the so-called merit order dilemma of emissions, the results were discussed for six representative countries. In a final analysis, the impact of carbon pricing was analyzed by calculating the Spearman correlation coefficient between prices and emissions along the merit order for different carbon prices.

The key findings of the paper are:

1. The great diversity of European countries in terms of the composition and the size of their national electricity supply systems is reflected in the XEFs and MEFs.
2. Price-based load shifts indicated that carbon emissions increased for 8 of the 20 countries and by 2.1% on average.
3. MEF-based load shifts led to average carbon emission savings of 35%, however decreasing the cost-saving potential by 56% compared to price-based load shifts.
4. Emissions and prices along the German merit order for the year 2019 decoupled with a carbon price of 42.6 €/t.
5. An carbon price increase from 0 to 156.1 €/t led to a switch between gas_cc and lignite/coal in the German merit order of 2019 and improved the carbon emission effect of the according price-based load shifts for European countries from a 10% increase to a 21% decrease.

Despite the limitations outlined in Section 3.6, the following main conclusions can be drawn:

1. Currently, DR could increase operational carbon emissions if spot-market prices are used as an incentive signal (under the current carbon price).
2. This phenomenon does not occur
   (a) if dynamic MEFs are used as DR incentive signal or
   (b) if an adequate carbon price is set.

While PBDR leads to negative environmental effects under specific circumstances, it is a very promising method of reducing operating cost and carbon emissions when adequate carbon prices are implemented. To exploit the full positive environmental potential of PBDR, high correlations between carbon intensity and marginal cost in the merit order need to be ensured either by adequate carbon prices or other market interventions.

In future research, the interconnectivity of individual countries to form a large interconnected network should be investigated, as this is an increasingly important aspect, which was however outside the scope of this paper. Furthermore, dynamic MEFs may be used for the assessment of the environmental potential of PBDR in real case studies considering technical, organizational, and process-related constraints in a realistic way.

CRediT authorship contribution statement

Markus Fleschutz: Conceptualization, Methodology, Software, Validation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Markus Bohlayer:** Conceptualization, Methodology, Writing - review & editing. **Marco Braun:** Supervision, Project administration, Funding acquisition. **Gregor Henze:** Writing - review & editing. **Michael D. Murphy:** Supervision, Conceptualization, 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.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.apenergy.2021.117040.

References

[1] The World Bank. What is carbon pricing? 2020, URL https://carbonpricingdashboard.worldbank.org/what-carbon-pricing.
[2] Hawkes AD. Long-run marginal CO2 emissions factors in national electricity systems. Appl Energy 2014;125:197–205. http://dx.doi.org/10.1016/j.apenergy.2014.03.060.
[3] Verzijlbergh RA, De Vries LJ, Dijkema GPJ, Herder PM. Institutional challenges caused by the integration of renewable energy sources in the European electricity sector. Renew Sustain Energy Rev 75;1364–0321. http://dx.doi.org/10.1016/j.rser.2016.11.039.
[4] DNV GL. Integration of renewable energy in Europe: A study on behalf of the European Commission. Technical report, 2014.
[5] Jordehi AR. Optimisation of demand response in electric power systems, a review. Renew Sustain Energy Rev 2019;103:308–19. http://dx.doi.org/10.1016/j.rser.2018.12.054.
[6] Good N, Ellis KA, Mancarella P. Review and classification of barriers and enablers of demand response in the smart grid. Renew Sustain Energy Rev 2017;72:57–72. http://dx.doi.org/10.1016/j.rser.2017.01.043.
[7] Paterakis NG, Erdinç O, Catalão JP. An overview of demand response: Key-elements and international experience. Renew Sustain Energy Rev 2017;69:871–91. http://dx.doi.org/10.1016/j.rser.2016.11.167.
[8] Siano P. Demand response and smart grids—A survey. Renew Sustain Energy Rev 2014;30:461–78. http://dx.doi.org/10.1016/j.rser.2013.10.022.
[9] Bohlayer M, Fleschutz M, Braun M, Zöttl G. Energy-intense production–inventory planning with participation in sequential energy markets. Appl Energy 2020;258:113954. http://dx.doi.org/10.1016/j.apenergy.2019.113954.
[10] Khan I, Jack MW, Stephenson J. Analysis of greenhouse gas emissions in electricity systems using time-varying carbon intensity. J Cleaner Prod 2018;184:1091–101. http://dx.doi.org/10.1016/j.jclepro.2018.02.309.
[11] Baumgärtner N, Delorme R, Hennen M, Bardow A. Design of low-carbon utility systems: Exploiting time-dependent grid emissions for climate-friendly demand-side management. Appl Energy 2019;247:755–65. http://dx.doi.org/10.1016/j.apenergy.2019.04.029.
[12] Kopsakangas-Savolainen M, Mattinen MK, Manninen K, Nissinen A. Hourly-based greenhouse gas emissions of electricity – cases demonstrating possibilities for households and companies to decrease their emissions. J Cleaner Prod 2017;153:384–96. http://dx.doi.org/10.1016/j.jclepro.2015.11.027.
[13] Jiusto S. The differences that methods make: Cross-border power flows and accounting for carbon emissions from electricity use. Energy Policy 2006;34(17):2915–28. http://dx.doi.org/10.1016/j.enpol.2005.05.002.

[14] Hawkes AD. Estimating marginal CO2 emissions rates for national electricity systems. Energy Policy 2010;38(10):5977–87. http://dx.doi.org/10.1016/j.enpol.2010.05.053.

[15] Siler-Evans K, Azevedo IL, Morgan MG. Marginal emissions factors for the U.S. electricity system. Environ Sci Technol 2012;46(9):4742–8. http://dx.doi.org/10.1021/es300145v.

[16] Corradi O. Marginal emissions: What they are, and when to use them. 2019, URL https://medium.com/electricitymap/ecd050ab0962.

[17] Regett A, Baing F, Conrad J. Emission assessment of electricity: Mix vs. marginal power plant method. In: 2018 15th international conference on the European energy market. Piscataway, NJ: IEEE; 2017, p. 1–5. http://dx.doi.org/10.1109/EEM.2018.8469940.

[18] Tranberg B, Corradi O, Lajoie B, Gibon T, Staffell I, Andresen GB. Real-time carbon accounting method for the European electricity markets. Energy Strategy Rev 2019;26:100367. http://dx.doi.org/10.1016/j.esr.2019.100367.

[19] Rinne S, Syri S. Heat pumps versus combined heat and power production as CO2 reduction measures in Finland. Energy 2013;57:308–18. http://dx.doi.org/10.1016/j.energy.2013.05.033.

[20] Pareschi G, Georges G, Boulouchos K. Assessment of the marginal emission factor associated with electric vehicle charging. http://dx.doi.org/10.3929/ETHZ-B-000200058.

[21] Péan T, Salom J, Ortiz J. Environmental and economic impact of demand response strategies for energy flexible buildings. In: Proceedings BSO 2018. vol. 4, 2018. p. 277–83.

[22] Khan I. Greenhouse gas emission accounting approaches in electricity generation systems: A review. Atmos Environ 2019;200:131–41. http://dx.doi.org/10.1016/j.atmosenv.2018.12.005.

[23] Summerbell DL, Khripko D, Barlow C, Hesselbach J. Cost and carbon reductions from industrial demand-side management: Study of potential savings at a cement plant. Appl Energy 2017;197:100–13. http://dx.doi.org/10.1016/j.apenergy.2017.03.083.

[24] Stoll P, Brandt N, Nordström L. Including dynamic CO2 intensity with demand response. Energy Policy 2014;65:490–500. http://dx.doi.org/10.1016/j.enpol.2013.10.044.

[25] Leerbeck K, Bacher P, Junker RG, Tveit A, Corradi O, Madsen H, et al. Control of heat pumps with CO2 emission intensity forecasts. Energies 2020;13(11):2851. http://dx.doi.org/10.3390/en13112851.

[26] WattTime. Automated emissions reduction. 2020, [cited 15.11.2020]. URL https://www.watttime.org/aer/.

[27] Tomorrow. electricityMap API. 2020, [cited 15.11.2020]. URL https://api.electricitymap.org/.

[28] ENTSOE. ENTSOE transparency platform. 2020, [cited 01.04.2020]. URL https://transparency.entsoe.eu.

[29] Doucette RT, McCulloch MD. Modeling the CO2 emissions from battery electric vehicles given the power generation mixes of different countries. Energy Policy 2011;39(2):803–11. http://dx.doi.org/10.1016/j.enpol.2010.10.054.

[30] Ryan NA, Johnson JX, Keoleian GA. Comparative assessment of models and methods to calculate grid electricity emissions. Environ Sci Technol 2016;50(17):8937–53. http://dx.doi.org/10.1021/acs.est.5b05216.

[31] Messagie M, Mertens J, Oliveira L, Rangaraju S, Sanfelix J, Coosemans T, et al. The hourly life cycle carbon footprint of electricity generation in Belgium, bringing a temporal resolution in life cycle assessment. Appl Energy 2014;134:469–76. http://dx.doi.org/10.1016/j.apenergy.2014.08.071.

[32] Roux C, Schalbart P, Peuportier B. Accounting for temporal variation of electricity production and consumption in the LCA of an energy-efficient house. J Cleaner Prod 2016;113:532–40. http://dx.doi.org/10.1016/j.jclepro.2015.11.052.

[33] Kono J, Ostermeyer Y, Wallbaum H. The trends of hourly carbon emission factors in Germany and investigation on relevant consumption patterns for its application. Int J Life Cycle Assess 2017;22(10):1493–501. http://dx.doi.org/10.1007/s11367-017-1277-z.

[34] Clauß J, Stinner S, Solli C, Lindberg KB, Madsen H, Georges L. Evaluation method for the hourly average CO2eq. Intensity of the electricity mix and its application to the demand response of residential heating. Energies 2019;12(7):1345. http://dx.doi.org/10.3390/en12071345.

[35] Munné-Collado I, Aprà FM, Olivella-Rosell P, Villafáfila-Robles R. The potential role of flexibility during peak hours on greenhouse gas emissions: A life cycle assessment of five targeted national electricity grid mixes. Energies 2019;12(23):4443. http://dx.doi.org/10.3390/en12234443.

[36] Greensfelder EM, Henze GP, Cushing VJ. Towards optimizing building energy use to reduce electric system carbon emissions. In: Proceedings of the ASME 4th international conference on energy sustainability - 2010. New York, NY: ASME; 2010, p. 999–1008. http://dx.doi.org/10.1115/ES2010-90141.

[37] Thomson RC. Carbon and energy payback of variable renewable generation. (Ph.D. thesis), Edinburgh: University of Edinburgh; 2014.

[38] Thomson RC, Harrison GP, Chick JP. Marginal greenhouse gas emissions displacement of wind power in Great Britain. Energy Policy 2017;101:201–10. http://dx.doi.org/10.1016/j.enpol.2016.11.012.

[39] Bettle R, Pout CH, Hitchin ER. Interactions between electricity-saving measures and carbon emissions from power generation in England and Wales. Energy Policy 2006;34(18):3434–46. http://dx.doi.org/10.1016/j.enpol.2005.07.014.

[40] Böing F, Regett A. Hourly CO2 emission factors and marginal costs of energy carriers in future multi-energy systems. Energies 2019;12(12):2260. http://dx.doi.org/10.3390/en12122260.

[41] Harmsen R, Graus W. How much CO2 emissions do we reduce by saving electricity? A focus on methods. Energy Policy 2013;60:803–12. http://dx.doi.org/10.1016/j.enpol.2013.05.059.

[42] Tomorrow. electricityMap. 2020, [cited 15.11.2020]. URL https://www.electricitymap.org/map.

[43] Fleschutz M. DrafProject/marginal-emission-factors: Marginal emission factors for 20 European countries. 2021, http://dx.doi.org/10.5281/zenodo.4718362.

[44] EnergieID. Entsoe-py: A Python client for the ENTSO-E API (European network of transmission system operators for electricity). 2020, [cited 11.09.2020]. URL https://github.com/EnergieID/entsoe-py.

[45] Hirth L, Mühlenpfordt J, Bulkeley M. The ENTSO-E transparency platform – A review of Europe's most ambitious electricity data platform. Appl Energy 2018;225:1054–67. http://dx.doi.org/10.1016/j.apenergy.2018.04.048.

[46] Open Power System Data. Data Package Conventional power plants: (Primary data from various sources, for a complete list see URL). 2018, https://doi.org/10.25832/conventional_power_plants/2018-12-20.

[47] Global Energy Observatory. Information on Global Energy Systems and Infrastructure. 2020, [cited 01.04.2020]. URL http://globalenergyobservatory.org/.

[48] Wikipedia. List of power stations in Serbia. 2020, URL https://en.wikipedia.org/w/index.php?oldid=944728190.

[49] EEX. European Emission Allowances Auction (EUA) Primary Market. 2019, [cited 18.02.2020]. URL https://www.eex.com/en/market-data/environmental-markets/auction-market/european-emission-allowances-auction#!/2020/02/17.

[50] Quaschning V. Regenerative energiesysteme: Technologie – Berechnung – Klimaschutz. 10th ed.. 2019.

[51] Konstantin P. Praxisbuch Energiewirtschaft. Berlin, Heidelberg: Springer Berlin Heidelberg; 2017, http://dx.doi.org/10.1007/978-3-662-49823-1.

[52] Statistische Bundesamt. Daten zur Energiepreisentwicklung - Lange Reihe von Januar 2005 bis Dezember 2019. URL https://www.destatis.de/DE/Themen/Wirtschaft/Preise/Publikationen/Energiepreise/energiepreisentwicklung-pdf-5619001.pdf?_blob=publicationFile.

[53] Mineralöl Franken. Produktspezifikation Heizöl DIN 51603 - EL -1 -Standard. 2003, [cited 01.04.2020]. URL https://www.mineraloel-franken.de/fileadmin/redaktion/downloads/Produktspezifikation_Heizoel_EL_Total.pdf.

[54] sandbag. EUA price: (Raw data from ICE via Quandl.). 2010, [cited 01.04.2020]. URL https://sandbag.org.uk/carbon-price-viewer/.

[55] The World Bank. DataBank: World Development Indicators: Electric power transmission and distribution losses (% of output) (EG.ELC.LOSS.ZS). 2020, [cited 19.05.2020]. URL https://databank.worldbank.org/reports.aspx?source=2&series=EG.ELC.LOSS.ZS.

[56] Statistisches Bundesamt. Daten zur Energiepreisentwicklung - Lange Reihen bis März 2020. 2020, [cited 01.04.2020]. URL https://www.destatis.de/DE/Themen/Wirtschaft/Preise/Publikationen/Energiepreise/energiepreisentwicklung-pdf-5619001.html.

[57] Corradi O. Estimating the Marginal Carbon Intensity of Electricity with Machine Learning. 2018, URL https://medium.com/electricitymap/49eade43b421.

[58] Matthey A, Bünger B. Cost Rates: Methodological Convention 3.0 for the Assessment of Environmental Costs: Version 02/2019.

[59] Böing F, Regett A, Kranner C, Pellinger C, Fattler S, Conrad J. Das Merit-Order-Dilemma der Emissionen: Eine Diskussionsgrundlage zur klimapolitischen Debatte. URL https://www.ffe.de/attachments/article/757/Arbeitspapier_Merit%20Order_Emissionen_Version_Februar_2019.pdf.