

The trends of hourly carbon emission factors in Germany and investigation on relevant consumption patterns for its application

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Abstract

Purpose The share of variable renewable energy sources (vRES) in the German electricity grid has increased over the past few decades. Due to the nature of the generation pattern of vRES, the increase of vRES causes the emission factor (EF) to fluctuate on an hourly basis. This fluctuation raises concerns about the accuracy of quantifying emissions with the current metric of the annual average EF as the respective EF may change depending on the time at which it is consumed.

Methods The study calculated the hourly EF of Germany from 2011 to 2015 and investigated the effect of an increase of vRES on the EF. The calculated hourly EF was clustered based on three aspects of time: the period of time, the time of a day, and the day of the week.

Results and discussion The study showed a higher proportion of vRES on weekend daytimes while the weekday nighttimes resulted in a lower share than the annual average. The study highlighted potential underestimation and overestimation of emissions by using annual average EF which ranged from +22% (2015 weekday nighttime of October) to -34% (2015 weekend daytime of May).

Conclusions The study suggested that the application of hourly EF may be necessary to quantify the respective emission from the consumers that use electricity during the weekend daytime and weekend nighttime. For consumer use at other times, the emissions could be quantified appropriately by using the conventional annual average EF.

Keywords Climate change · Consumption pattern · Dynamic LCI · Emission factor · Environment

1 Introduction

Electricity is one of the key inventories in a life cycle assessment (LCA); it is frequently used to describe the life cycle inventory (LCI) of various products (Mendoza et al. 2012; Torrellas et al. 2012; Treyer and Bauer 2016). The prevalence of the electricity inventory's use in LCA studies suggests that the accuracy of the inventory may significantly impact the result of an LCA. There exists a tremendous variety of electricity inventories in ecoinvent, with 71 geographical regions being represented (Weidema et al. 2013). Currently, the inventory of electricity is based on the annual share of energy sources in the electricity grid mix of a country. Based on this mix, the annual average carbon emission factor (EF) of electricity is calculated and used to quantify the emission from consumed electricity.

However, the electricity mix has changed rapidly over the last few decades in response to the emission reduction goals set by many countries to combat climate change. For example, the EU set the emission reduction target of 20% by 2020 through the Climate and Energy Package (Commission of the European Communities 2008). In keeping with the commitments outlined, the share of renewable energy sources in the electricity grids increased in several countries. Germany is one of the countries that has successfully increased their share of renewables in the grid. As a result, the grid mix of Germany has transformed over the previous few decades.

The share of renewable energy increased from 3% in 1990 to 30% in 2015 (BDEW 2016; BMU 2013; Morris and Peht 2015). In other words, the share of renewable energy in the German electricity grid increased tenfold in 25 years (BDEW

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2016; BMU 2013). Within the increased share of overall renewable energy, the contribution of variable renewable energy sources (vRES), such as solar and wind, was significant. The electricity generation from vRES is dependent on the time when the energy sources are available, which restricts the ability to plan electricity generation in the same manner as is possible with conventional power plants. As a consequence of the increased share of such renewables in the grid, a variation of the electricity grid mix could be expected depending on the time of day. In fact, the study by Paraschiv et al. (2014) offers that the renewable energies in the electricity spot market enhances the deviation in price in Germany.

With the energy mix varying with increased vRES, the corresponding carbon emission by consuming 1 kWh of electricity may change depending on the time. This indicates the weakness of the current usage of annual average EF for quantifying emission from electricity consumption, depending on when the electricity is consumed. Indeed, previous studies state the lack of temporal information in LCA as an important limitation of LCA (Levasseur et al. 2010; Pinsonnault et al. 2014; Reap et al. 2008). To better quantify the respective emission for a specific consumer, higher resolutions of EFs may become relevant. Moreover, with the increase of vRES in Germany as well as various European countries such as Denmark, Italy, and Spain (Eurostat 2016), the importance of yielding a higher resolution of EF of electricity may become relevant for other countries as well. With the adoption of the Paris Agreement in COP21 (UNFCCC 2016), the uptrend in share of vRES can likely be expected in other nations and continents as well.

Recent studies have generated a higher resolution of carbon EFs of electricity for Belgium (Messagie et al. 2014) and Canada (Cubi et al. 2015). However, the German grid system is somewhat unique in its sizeable share of vRES and the size of the power market, which renders the country an interesting case study for assessing the effect of the higher resolution on EF on quantifying carbon emissions. Therefore, this study calculated an hourly resolution of the carbon EF of the German electricity grid mix to assess the relevance of the time of day when the electricity is consumed. To quantify the EF, a life cycle impact assessment (LCIA) was made for each power source. The hourly EF of 5 years (2011–2015) was clustered in various time resolutions based on the period of time, the day of the week, and the time of day. With the clustering, the study intended to highlight that the use of hourly EF grows in significance depending on the consumption patterns of a consumer.

2 Methods

The hourly electricity generation data for Germany was used to calculate the hourly EFs. Based on the energy mix of the

generation data, the hourly EF was calculated. The following section introduces the source and method for calculating the averaged EFs.

2.1 Data sources for generation

The hourly electricity generation data for the German electricity grid was sourced from the EEX (European Energy Exchange AG 2015). The data represents the net electricity generation of a specific hour from companies participating in the wholesale electricity market of EEX. In Table 1, the German national statistics of the gross electricity generation and the share of generation data covered by the study are depicted. Due partly to the fact that not all electricity generation facilities are represented in the EEX market, and partly to the differing representations of generation data, the data in the study represented about 65% of the gross German electricity generation (BDEW 2016). For the studied years, the representation of the electricity generated from renewables covered in the study amounted to about 60% of the gross electricity generation of renewables in Germany, which was slightly lower than that of the overall generation. Therefore, the study can be considered to draw conservative rather than optimistic results regarding the EFs. The study did not consider the import and the export of the electricity between the neighboring countries.

2.2 Data sources for emission

The LCI datasets for each energy source from ecoinvent v3.1 were used to quantify the hourly EF of electricity (Weidema et al. 2013), and the global warming potential (GWP) based on IPCC (2013) was calculated via SimaPro (PRé Consultants 2015). The LCIA was based on a cradle-to-factory gate system boundary. The LCI datasets of electricity from ecoinvent and calculated LCIA is shown in Table 2.

For the electricity from nuclear energy, hourly generation data from EEX was only available as an aggregated value comprising data from pressurized water reactors (PWR) and boiling water reactors (BWR). Thus, the ratio of annual generation volume of PWR (78%) and BWR (21%) (Deutsches Atomforum e. V. 2015) was applied to quantify the hourly emission from nuclear energy. For the electricity classified in the “Other” category, the study chose biogas based on the description from EEX which mentioned the biomass as part of the category, while the category “Biomass” was represented by state-of-the-art biomass LCI dataset.

2.3 Emission factors in various resolutions

Since the share of energy source may vary in the electricity grid with the increased capacity of vRES, the study

Table 1 Gross electricity generation in Germany and rate of representation in the EEX market data from 2011 to 2015

	Annual generation		Generation from renewables		
	TWh	Covered rate in the study from EEX data (%)	TWh	Share of renewable in the grid mix (%)	Covered rate in the study from EEX data (%)
2011	613	65.19	137	22.35	63.85
2012	630	63.44	144	22.84	60.78
2013	639	65.17	152	23.86	59.38
2014	628	66.90	163	25.88	62.70
2015	652	74.05	196	30.04	67.65

investigated the variation of the EF in several time resolutions. In the study, carbon EFs were calculated as Eq. (1).

$$EF_t = \frac{\sum GWP_t}{\sum G_t} \tag{1}$$

where *EF* represents the carbon EF, *GWP* represents the emitted global warming potential from the entire electricity grid, and *G* represents the total electricity generation of the grid at a given time *t*. The highest resolution of time *t* was hourly.

The EFs were clustered based on three aspects: the length of the time period, the time of day, and the day of the week. Each of the clustered EF was calculated based on Eq. (1). Thus, rather than averaging the hourly EF over the respective period, the clustered EF represents corresponding emission and generation that took place during the represented period. Regarding the length of the time period, the study calculated EF for annual, monthly, and hourly resolution. The influence

of the time of day was isolated by defining “daytime” and “nighttime”. For the study, 6:00–18:00 was defined as the “daytime”, while the rest of the hours were regarded as “nighttime”. The EF of weekdays (Monday to Friday) and weekends (Saturday and Sunday) were also calculated with Eq. (1). Thus, the study investigated the potential deviation of clustered average EFs from the annual average to assess the accuracy of quantifying the emission using annual average EFs.

In order to consider the electricity measures from the consumer perspective, the losses that occurred in the grid were included. In ecoinvent, the losses along the transmission and infrastructure for the grid were accounted for in the transformation from high voltage to low voltage. The transmission loss was considered to be 2.6% for the German data. The difference between the high voltage and low voltage electricity mix for German electricity EF was 2.7%, which demonstrates the limited relevance of grid infrastructure compared to the losses occurring in the grid. According to the World Bank

Table 2 Energy sources for German electricity grid mix and GWP of each LCI

Energy source in EEX	LCI in ecoinvent	GWP [gCO ₂ eq/kWh]
Coal	Electricity, high voltage {DE} electricity production, hard coal Alloc Def, U	1112.06
Coal derived gas	Electricity, high voltage {DE} electricity production, hard coal Alloc Def, U	1112.06
Gas	Electricity, high voltage {DE} electricity production, natural gas, at conventional power plant Alloc Def, U	588.52
Lignite	Electricity, high voltage {DE} electricity production, lignite Alloc Def, U	1234.70
Oil	Electricity, high voltage {DE} electricity production, oil Alloc Def, U	1150.68
Pumped-storage	Electricity, high voltage {DE} electricity production, hydro, pumped storage Alloc Def, U	951.52
Run-of-the-river	Electricity, high voltage {DE} electricity production, hydro, run-of-river Alloc Def, U	4.50
Seasonal-store	Electricity, high voltage {DE} electricity production, hydro, reservoir, non-alpine region Alloc Def, U	14.37
Nuclear	Electricity, high voltage {DE} electricity production, nuclear, boiling water reactor Alloc Def, U; Electricity, high voltage {DE} electricity production, nuclear, pressure water reactor Alloc Def, U	13.75
Other	Electricity, high voltage {DE} heat and power co-generation, biogas, gas engine Alloc Def, U	313.08
Garbage	Electricity, high voltage {DE} treatment of blast furnace gas, in power plant Alloc Def, U	819.47
Biomass	Electricity, high voltage {DE} heat and power co-generation, wood chips, 6667 kW, state-of-the-art 2014 Alloc Def, U	38.80
PV	Electricity, low voltage {DE} electricity production, photovoltaic, 3 kWp slanted-roof installation, single-Si, panel, mounted Alloc Def, U	93.25
Wind	Electricity, high voltage {DE} electricity production, wind, >3 MW turbine, onshore Alloc Def, U	32.98
Offshore wind	Electricity, high voltage {DE} electricity production, wind, 1–3 MW turbine, offshore Alloc Def, U	17.09

Table 3 Annual average EF, minimum and maximum hourly EF of each year for German electricity grid mix for 2011 to 2015 in gCO_{2eq}/kWh. Minimum and maximum EF are recorded in gCO_{2eq}/kWh and normalized values that take the annual average EF of respective year as the reference

Year	2011		2012		2013		2014		2015	
Annual average EF	675	100%	686	100%	708	100%	681	100%	676	100%
Min hourly EF	328	49%	351	51%	278	39%	250	37%	278	41%
Max hourly EF	928	138%	920	135%	980	138%	901	133%	951	141%

(World Bank 2016), the losses along the transmission and distribution grid in Germany from 2011 to 2013 totaled around 4.0%. In this study, the transmission loss of 4% was homogeneously applied to all energy sources for all of the investigated years when computing the EF.

3 Results and discussion of averaged emission factors

3.1 Analysis of annual average and hourly emission factors

With the data obtained from EEX and the use of Eq. (1), the hourly EF of 2011 to 2015 was derived. The annual average EF for each year was also calculated, and is displayed in Table 3. The table also includes the minimum and maximum hourly EF of each year, which is presented in both absolute value and normalized value based on the annual average EF of each respective year. In Fig. 1, the share of energy sources at the time when the minimum and maximum hourly EF occurred is depicted.

For the minimum hourly EF, the share of the vRES steadily increased each year from 43% in 2011 to 65% in 2015.

Fig. 1 The share of energy sources at the time when the minimum and maximum hourly EF took place in 2011 to 2015

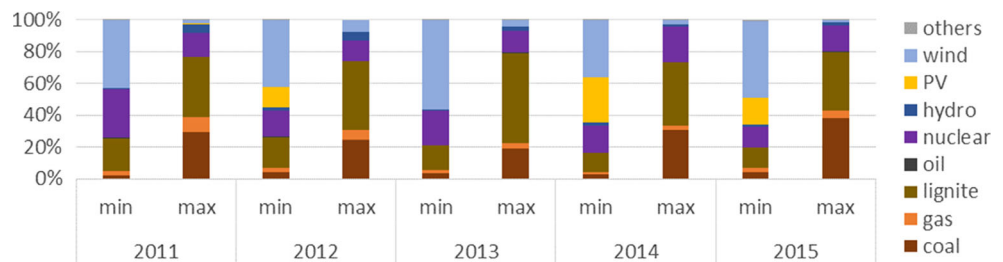
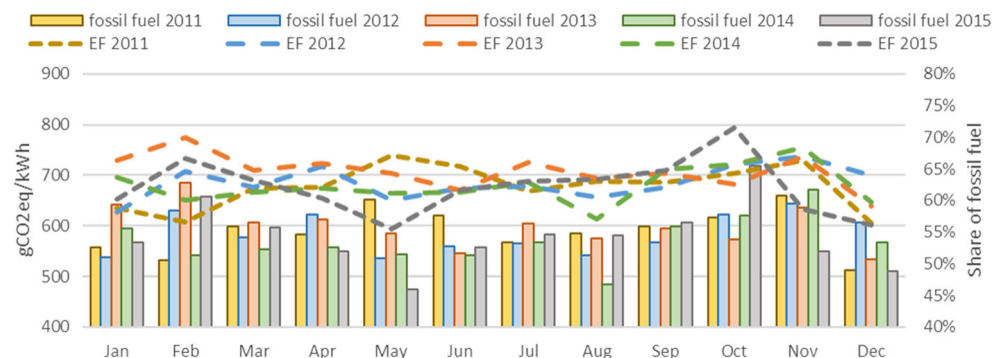


Fig. 2 Monthly average EF and the monthly average share of renewable energy in the German electricity grid mix for 2011 to 2015



Nevertheless, over the five investigated years, the lowest hourly EF took place in 2014 instead of 2015, although 2015 experienced the highest annual share of vRES. Moreover, the minimum hourly EF of 2015 was marginally higher than that of 2013, where 2015 had 9% less share of vRES. This was due to the increased share of coal and gas, with the reduction of nuclear power. However, since the data from EEX does not cover the entire generation volume in Germany, further study may be necessary for a higher accuracy and precision. Yet, the result demonstrated that the variation of the hourly EF over the years can deviate substantially from the annual average EF.

3.2 Monthly emission factors

Figure 2 illustrates the monthly average EF and the share of renewable energy in the grid from 2011 to 2015. Although the monthly average EF within a year fluctuated by nearly 30% between the minimum and maximum value, the month of the year appears not to be a reliable indication for a high or low EF. For instance, a relatively high monthly average EF was recorded during February 2012, 2013, and 2015, while this result was absent in 2011 and 2014. For the minimum monthly

Table 4 Annual average EFs subdivided into weekdays and weekends from 2011 to 2015. Annual average EF of each year was taken as a reference

Year	2011		2012		2013		2014		2015	
Unit	[gCO _{2eq} /kWh]	(%)	[gCO _{2eq} /kWh]	(%)	[gCO _{2eq} /kWh]	(%)	[gCO _{2eq} /kWh]	(%)	[gCO _{2eq} /kWh]	(%)
Weekly	675	100	686	100	708	100	681	100	676	100
Weekday	689	102	699	102	725	103	701	103	697	103
Weekend	635	94	647	94	656	93	623	91	615	91

average EF, January was the lowest in 2012, while December was the lowest in 2011 and 2013. In 2014, August was the lowest, and May in 2015 which were in completely different seasons of the year compared to the former 3 years.

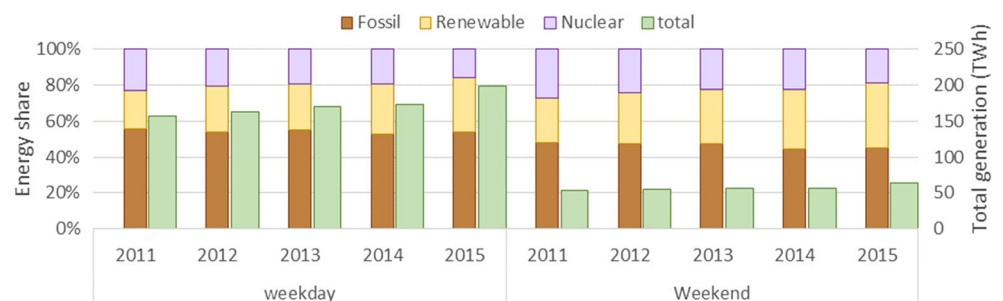
However, the deviation of the monthly average EF between the best and the worst month over the years tended to increase. In 2012, the difference of monthly average EF between January and November was 17% against the annual average EF. The difference between the best and worst monthly average EF increased to 20% in 2013, 21% in 2014, and 31% in 2015. These results indicated that with the increased share of renewable energy, in which vRES was the major contributor, the consideration of the month of electricity consumption becomes more important to the accuracy of quantifying the emission.

3.3 Difference between weekdays and weekends

In order to investigate the influence of the time of consumption from a different viewpoint, the relevance of the day of the week was studied. Table 4 illustrates the annual average EF, clustered based on the day of a week. In Fig. 3, the share of energy sources and the average daily volume of electricity generation for weekdays and weekends are presented.

The result showed that the annual average EF of the weekend was becoming “cleaner” than the overall average, by having a lower proportion of fossil fuel in the grid mix with a lower volume of generated electricity than the weekday. It is therefore clear that electricity consumed on the weekends was cleaner than the emission calculated using the annual average EF for the last 5 years. The finding suggests the overestimation of the quantified GHG emission of the weekend by nearly 10% when the annual average EF is used.

Fig. 3 Share of energy sources and average daily electricity generation volume for weekdays and weekends from 2011 to 2015



In Table 5, the monthly average EF subdivided into weekdays and weekends is presented from 2011 to 2015. The values were normalized by the annual average EF of each year.

The results revealed the increasing deviation of some cleaner monthly average EF of the weekend against the annual average EF over the years. In addition to the values from the weekend, some of the “dirtier” monthly average EF of the weekdays also experienced a greater deviation from the annual average EF. It is therefore possible that an increasing variation of the “cleanliness” of the grid mix depends on the day of the week and increased share of vRES. With some months experiencing a nearly 20% underestimation on weekdays and 25% of overestimation on weekends, the use of annual average EF for consumers with specific consumption patterns on the day of the week may be considered as inappropriate.

3.4 Difference between the daytime and nighttime

The last scope of investigation in relation to the time of consumption was the time of day. In Table 6, the annual average EF was clustered based on the time of day and the day of the week, which were normalized by the annual average EF. In Fig. 4, the share of energy sources and the average daily volume of electricity generation were clustered into four groups of daytimes and nighttimes of weekdays and weekends.

Demonstrably, the electricity user who consumes only during the daytime on the weekend would have their GHG emission overestimated by nearly 15% when the annual average EF was used to calculate the emissions in 2013 to 2015. This overestimation was due to the increased proportion of non-fossil fuel in the energy mix of the electricity through increased available volume of such energy sources, especially from both vRES. While the decrease of the total volume of

Table 5 Monthly average EF clustered based on day of the week, normalized by annual average EF

		Jan (%)	Feb (%)	Mar (%)	Apr (%)	May (%)	Jun (%)	Jul (%)	Aug (%)	Sep (%)	Oct (%)	Nov (%)	Dec (%)
2011	Weekly	94.00**	90.10**	100.00	100.30	109.40*	106.20*	98.90	102.00	101.70	104.20	108.10*	89.80**
	Weekday	97.70	93.30**	100.40	101.50	112.60*	108.90*	103.80	102.70	101.80	104.10	111.00*	91.60**
	Weekend	85.40**	80.90**	98.70	96.90	100.40	97.80	87.40**	99.50	101.50	104.20	99.50	84.70**
2012	Weekly	91.60**	103.10	98.70	104.60	94.80**	98.30	98.80	95.80	98.60	105.30*	107.60*	102.00
	Weekday	92.80**	103.60	101.90	107.70*	96.40	102.20	100.80	98.10	100.10	106.80*	108.70*	104.20
	Weekend	87.90**	101.90	89.10**	95.80	89.40**	87.90**	93.00**	88.30**	95.00	100.20	104.10	97.00
2013	Weekly	103.10	109.50*	100.20	102.10	99.40	94.70**	102.50	98.10	99.50	96.40	104.10	90.40**
	Weekday	103.10	110.10*	105.30*	102.90	102.10	100.90	104.90	101.60	101.70	97.50	106.70*	93.60**
	Weekend	103.10	107.90*	88.00**	99.60	90.20**	79.00**	94.20**	88.30**	93.50**	92.40**	97.40	81.60**
2014	Weekly	102.30	95.70	97.90	98.90	97.70	98.00	100.60	90.00**	104.70	106.00*	110.90*	95.10
	Weekday	105.00	101.40	102.00	100.90	100.70	100.60	102.50	93.90**	105.40*	108.50*	115.20*	96.40
	Weekend	93.40**	79.90**	87.90**	92.40**	88.90**	90.80**	94.30**	80.70**	102.30	97.10	100.40	91.00**
2015	Weekly	96.30	108.40*	101.90	96.70	87.90**	99.10	101.80	102.40	104.90	117.40*	93.60**	88.80**
	Weekday	99.00	112.20*	104.10	98.70	92.50**	101.90	103.40	105.00	108.00*	119.00*	97.70	93.70**
	Weekend	88.90**	97.30	95.30	89.80**	76.20**	89.50**	96.50	95.60	94.70**	112.80*	82.70**	73.30**

*The values higher than 105%

**The values lower than 95%

Table 6 Normalized annual average EF of the time of a day and the day of the week for 2011 to 2015

	2011		2012		2013		2014		2015	
	Day (%)	Night (%)	Day (%)	Night (%)	Day (%)	Night (%)	Day (%)	Night (%)	Day (%)	Night (%)
Weekly	98.2	102.1	96.2	104.6	95.8	105.0	95.5	105.5	96.0	104.8
Weekday	100.8	103.7	98.8	105.9	98.8	107.0	98.9	107.8	99.4	107.4
Weekend	90.5	97.9	88.5	101.0	86.8	99.4	84.9	99.1	85.3	97.3

produced electricity more significantly affected the proportion of the non-fossil fuel between weekdays and weekends, the increase of volume of non-fossil fuel energy sources exerted more influence in the daytime than the nighttime. On the weekend, the difference in generated electricity volume between the daytime and nighttime over the year was around 5%, whereas the difference in the share of fossil fuel in the

mix was nearly 10%. Thus, the inaccuracy of using the annual average EF to calculate the emission of daytime electricity consumers on weekends in a grid where the share of vRES, mainly from solar energy, is expected to increase.

On the other hand, the individuals who consumed electricity during the nighttime on weekdays experienced emission underestimation of nearly 7% when calculating emissions through

Fig. 4 Share of energy sources and average daily electricity generation volume for the daytime and the nighttime of weekdays and weekends from 2011 to 2015

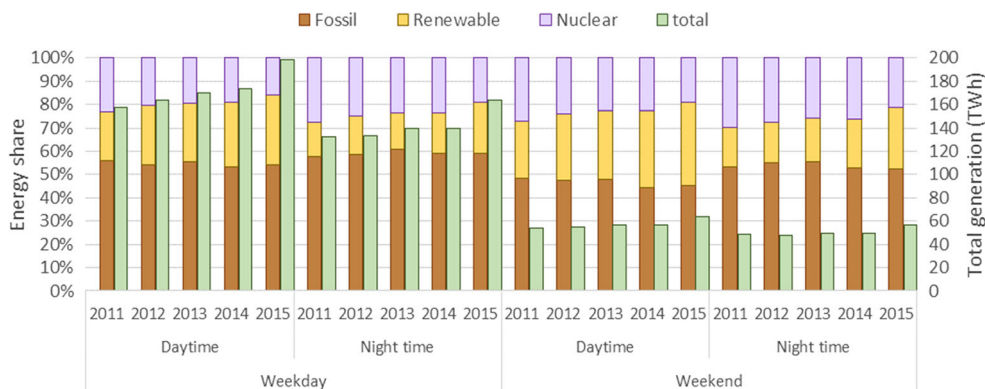


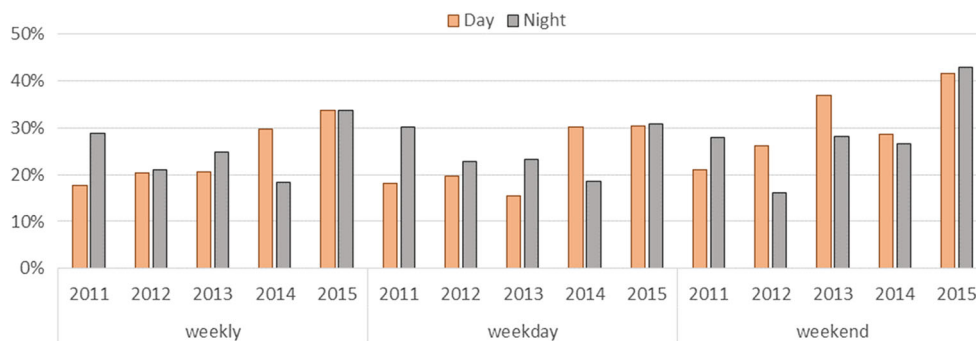
Table 7 Monthly EF clustered in weekday, weekend, daytime and nighttime normalized by annual EF for 2011 to 2015

			Jan (%)	Feb (%)	Mar (%)	Apr (%)	May (%)	Jun (%)	Jul (%)	Aug (%)	Sep (%)	Oct (%)	Nov (%)	Dec (%)
2011	Weekly	Daily	94.00**	90.10**	100.00	100.30	109.40*	106.20*	98.90	102.00	101.70	104.20	108.10*	89.80**
		Day	95.80	91.00**	97.70	96.40	103.70	102.20	95.10	97.70	98.20	102.50	108.50*	91.30**
		Night	92.00**	89.00**	102.60	105.00	116.70*	111.10*	103.50	107.10*	106.00*	106.10*	107.80*	88.00**
	Weekday	Daily	97.70	93.30**	100.40	101.50	112.60*	108.90*	103.80	102.70	101.80	104.10	111.00*	91.60**
		Day	95.80	91.00**	97.70	96.40	103.70	102.20	95.10	97.70	98.20	102.50	108.50*	91.30**
		Night	94.60**	91.60**	102.40	105.50*	119.30*	113.00*	108.20*	107.50*	105.70*	105.20*	110.20*	89.30**
	Weekend	Daily	85.40**	80.90**	98.70	96.90	100.40	97.80	87.40**	99.50	101.50	104.20	99.50	84.70**
		Day	84.50**	79.90**	94.60**	91.20**	92.70**	91.70**	82.40**	93.90**	97.00	100.60	98.40	84.70**
		Night	86.20**	82.00**	103.10	103.40	109.60*	105.00	93.10**	105.90*	106.70*	108.30*	100.70	84.60**
2012	Weekly	Daily	91.60**	103.10	98.70	104.60	94.80**	98.30	98.80	95.80	98.60	105.30*	107.60*	102.00
		Day	92.30**	102.00	94.50**	99.00	87.70**	91.50**	91.40**	88.80**	92.60**	102.60	108.10*	102.80
		Night	90.80**	104.40	103.70	111.50*	104.40	107.40*	108.70*	104.80	106.10*	108.40*	107.10*	101.20
	Weekday	Daily	92.80**	103.60	101.90	107.70*	96.40	102.20	100.80	98.10	100.10	106.80*	108.70*	104.20
		Day	92.30**	102.00	94.50**	99.00	87.70**	91.50**	91.40**	88.80**	92.60**	102.60	108.10*	102.80
		Night	91.10**	103.90	106.50*	113.80*	105.60*	109.90*	110.20*	106.40*	106.60*	109.50*	108.00*	102.60
	Weekend	Daily	87.90**	101.90	89.10**	95.80	89.40**	87.90**	93.00**	88.30**	95.00	100.20	104.10	97.00
		Day	86.20**	98.30	83.30**	87.90**	81.00**	77.90**	83.90**	79.00**	86.70**	95.80	104.00	96.20
		Night	89.70**	105.80*	95.80	105.10*	100.10	100.80	104.40	99.80	104.90	105.10*	104.20	97.90
2013	Weekly	Daily	103.10	109.50*	100.20	102.10	99.40	94.70**	102.50	98.10	99.50	96.40	104.10	90.40**
		Day	103.80	108.30*	95.90	95.50	92.90**	87.60**	92.80**	89.90**	94.60**	94.40**	103.80	90.20**
		Night	102.40	110.90*	105.10*	110.40*	107.90*	104.20	115.50*	108.70*	105.40*	98.70	104.50	90.60**
	Weekday	Daily	103.10	110.10*	105.30*	102.90	102.10	100.90	104.90	101.60	101.70	97.50	106.70*	93.60**
		Day	103.80	108.30*	95.90	95.50	92.90**	87.60**	92.80**	89.90**	94.60**	94.40**	103.80	90.20**
		Night	102.10	111.20*	109.80*	110.70*	109.60*	109.30*	116.90*	111.50*	107.00*	99.70	106.80*	93.70**
	Weekend	Daily	103.10	107.90*	88.00**	99.60	90.20**	79.00**	94.20**	88.30**	93.50**	92.40**	97.40	81.60**
		Day	102.60	105.70*	82.50**	91.30**	80.50**	68.70**	81.20**	78.10**	86.80**	89.50**	96.20	80.80**
		Night	103.70	110.10*	94.10**	109.30*	102.10	91.90**	110.80*	100.90	101.30	95.50	98.60	82.60**
2014	Weekly	Daily	102.30	95.70	97.90	98.90	97.70	98.00	100.60	90.00**	104.70	106.00*	110.90*	95.10
		Day	102.90	93.90**	92.30**	91.20**	89.30**	88.20**	91.80**	81.60**	99.00	103.90	111.20*	96.00
		Night	101.70	97.60	104.60	108.80*	108.80*	111.20*	112.40*	101.20	111.80*	108.40*	110.50*	94.10**
	Weekday	Daily	105.00	101.40	102.00	100.90	100.70	100.60	102.50	93.90**	105.40*	108.50*	115.20*	96.40
		Day	102.90	93.90**	92.30**	91.20**	89.30**	88.20**	91.80**	81.60**	99.00	103.90	111.20*	96.00
		Night	104.70	102.10	108.50*	110.00*	110.50*	112.90*	113.40*	104.20	111.70*	110.40*	114.00*	95.50
	Weekend	Daily	93.40**	79.90**	87.90**	92.40**	88.90**	90.80**	94.30**	80.70**	102.30	97.10	100.40	91.00**
		Day	94.60**	74.70**	81.20**	82.00**	77.40**	78.40**	82.70**	70.00**	93.90**	93.00**	98.40	92.20**
		Night	92.30**	85.70**	95.40	105.00	103.80	106.70*	109.10*	94.40**	112.20*	101.70	102.50	89.80**
2015	Weekly	Daily	96.30	108.40*	101.90	96.70	87.90**	99.10	101.80	102.40	104.90	117.40*	93.60**	88.80**
		Day	96.50	106.70*	97.70	88.50**	80.70**	92.20**	93.00**	94.80**	100.30	114.30	94.90**	90.30**
		Night	96.20	110.20*	106.90*	106.90*	97.20	108.10*	113.00*	111.70*	110.40*	120.90*	92.30**	87.20**
	Weekday	Daily	99.00	112.20*	104.10	98.70	92.50**	101.90	103.40	105.00	108.00*	119.00**	97.70	93.70**
		Day	96.50	106.70*	97.70	88.50**	80.70**	92.20**	93.00**	94.80**	100.30	114.30*	94.90**	90.30**
		Night	98.40	114.10*	109.40*	108.60*	101.00	110.10*	114.00*	113.00*	112.70*	122.00*	96.40	91.20**
	Weekend	Daily	88.90**	97.30	95.30	89.80**	76.20**	89.50**	96.50	95.60	94.70**	112.80*	82.70**	73.30**
		Day	87.70**	95.30	91.30**	80.30**	66.60**	79.40**	85.50**	84.70**	87.30**	108.10*	83.70**	71.70**
		Night	90.20**	99.40	99.60	101.00	87.90**	101.40	109.40*	108.50*	103.10	117.80*	81.70**	75.10**

*The values higher than 105%

**The values lower than 95%

Fig. 5 Difference between maximum and minimum monthly average EF for each cluster of time resolution for 2011 to 2015



annual average EF in 2012 to 2015. The decreased share of renewable energy, primarily from solar, in the grid mix clearly affected the “cleanliness” of the consumed electricity.

Table 7 depicts the results further broken down into months. In Fig. 5, the maximum differences among the monthly average EFs for each cluster are given.

The results of clustering the monthly average EF into the time of day and the day of the week depicted that the range of underestimation and overestimation varied from 22% (2015 weekday nighttime of October) and 34% (2015 weekend daytime of May), respectively. The result did not exhibit clear trends for specific months, as noted in Chapter 3.2. Nonetheless, from March to September, the EF of weekday daytime was generally less than the annual average EF (up to 15%), and weekend daytime was around 20% less. Another clear tendency demonstrated in Fig. 5 was the increasing deviation of minimum and maximum monthly average EF for each cluster of time, especially the decrease of EF during the daytime. The increasing EF difference suggests the increasing inaccuracy of quantifying GHG emission with the annual average EF for electricity consumers with varying demands over the months during the daytime with the higher grid share of vRES.

3.5 Uncertainty in the result

The study is possibly affected by several aspects of uncertainty that might influence the obtained results. The first aspect of uncertainty was the exclusion of the import and export of electricity between the neighboring grids. According to BDEW (2016), the amount of export that took place between 2011 and 2015 was around 55 to 85 TWh, where the amount of import was around 30 to 50 TWh. While the share of export increased from 9 to 13% of the gross electricity generation for the respective years, the share of import decreased from 8 to 5%. Since the inflow of electricity from neighboring grids involves its own mixes and corresponding EFs, the decreasing share of the import implies the decreasing uncertainty of the calculated EF.

Another factor of uncertainty was the sample size of the weekends of each month, which is less than 10 days in

Chapter 3.4. With such a limited sample size, the effect of extreme weather events, for instance, may play a significant role in the corresponding EF, especially for vRES.

4 Conclusions

In light of the recent increase of vRES in the German electricity grid, the study calculated the higher temporal resolution of the grid mix from 2011 to 2015. The study assessed the accuracy of the quantified emissions by using the annual average EF through different clusters of time. In the study, the increase of vRES, which was the main source for the increase of renewable energy as a whole, was demonstrated. This affected the variation of the “cleanliness” of hourly EF over the years. This observation suggested the increasing importance of applying the hourly EF over annual average EF with the increase of vRES in the grid for accurate quantification of emission.

Moreover, the study revealed that weekend daytime consumers may have their emissions overestimated by the annual average EF, while the weekday nighttime consumers may have been underestimated. The difference in EF between the days of the week increased over the years. The increase of vRES may have played an important role in this increase. Furthermore, the accuracy of calculating the emission of daytime and nighttime was also affected by the increase of the vRES, where the deviation of these two EFs from the annual average EF was generally increasing. This implies the weakness of applying the annual average EF on consumers who typically use the electricity during the weekday nighttime or weekend daytime. The study also found that when the consumption volume differs from month to month, the inaccuracy of quantified emission may rise, which was evident from the monthly average EF results.

On the other hand, the weekday daytime EF recorded very similar values to the annual average EF, suggesting the appropriateness of the use of the annual average EF for quantifying the emission of the consumer who typically consumes electricity during the weekday daytime.

For future research, the influence of the increased vRES on the EFs may require further investigation. The influence may

be investigated by taking other countries such as Denmark, Italy, or Spain—which record high levels of penetration of vRES in the grid recently (Eurostat 2016)—as a case study. However, access to hourly generation data in the grid would be a challenge. The limitation of the study regarding the coverage of generation data may also be strengthened in the future. Furthermore, the limitation regarding the exchange of electricity between the neighboring countries may influence the cleanliness of the electricity. However, in order to account for the influence of taking inflow of electricity from neighboring grids into account, the EF of the inflow electricity will need to be included in the hourly resolution. Furthermore, the inclusion of neighboring grid electricity of Germany will call for further inclusion of grids surrounding the German neighboring grids as electricity in Europe is traded on a continental scale. This calls for the further investigation of the hourly EF of other grids to allow the inclusion of electricity from other grids.

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