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MARGINAL GRID EMISSIONS AND PRIMARY ENERGY TO ACTIVATE DEMAND SIDE MANAGEMENT: COVID19 CASE STUDY

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The construction of Marginal Emissions Factor (MEF) and Marginal Primary Energy Factor (MPEF) time series of the electricity grid can be used as an effective method to activate demand-side strategies in buildings and thus reducing their carbon footprint and primary energy use. The robustness of a method to calculate MEF and MPEF in function of the load and the share of renewables of the power grid is tested in the present work. The construction of the MEF and MPEF signals is applied to historical and pandemic data sets to investigate potential differences. A specific analysis in the period of the COVID-19. Daily profiles of the marginal and average emissions and primary energy during pandemic are compared with the pre-pandemic period. Preliminary results show that the full pandemic caused a reduced electricity demand by 13% with a reduction of overall assocaited MEF and MPEF of 50% and 35% respectively. Robustness of the methodology is measured by an average year correlation being 85% for pre-pandemic period, whereas pandemic periods reach about 70%. Demand response strategies as activated by the marginal signals can be used to reduce the carbon footprint and primary energy use of the built environment.

Keywords: Grid Emissions; Primary Energy Use; COVID19 ; Marginal Emissions Factor; Marginal Primary Energy Factor; Demand-side Management

EMISIONES Y ENERGÍA PRIMARIA MARGINALES DE LA RED ELÉCTRICA PARA ACTIVAR LA GESTIÓN DE LA DEMANDA: CASO DE ESTUDIO COVID19

La construcción de un factor de emisiones marginales (MEF) y de energía primaria marginal (MPEF) para series temporales puede usarse como método efectivo para activar la gestión de la demanda en edificios; reducir las emisiones y el uso de energía primaria (PE). El trabajo presente comprueba la consistencia de la metodología para el cálculo del MEF y MPEF en función de la carga y la proporción de renovables de la red eléctrica. La construcción de las señales MEF y MPEF es aplicada a datos históricos y pandémicos. Se realiza un análisis específico para los meses de COVID-19. Se comparan perfiles diarios de las emisiones y PE marginales y promedias durante la pandemia con el período histórico. Los resultados preliminares revelan una reducción del 13% en demanda energética junto con una reducción de MEF y MPEF del 50% y 35% respectivamente. La solidez de la metodología es determinada por la correlación de los años analizados, resultando en un promedio de 85% (históricos) y de 70% (pandémico). Las estrategias de gestión de la demanda como las activadas en la utilización de señales marginales pueden servir para reducir la huella de carbono y el uso de energía primaria del entorno construido.

Palabras clave: Emisiones Red Eléctrica; Uso Energía Primaria; COVID19; Factor de Emisiones Marginales; Factor de Energía Primaria Marginal; Gestión de la Demanda

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1. Introduction

Current energy and greenhouse gas emissions assessments in the building sector do not account for the variable performance of the electric grid. Incorporating hourly grid variability into building assessment methods can help to better prioritize energy efficiency measures that may result in largest environmental benefits (Cubí et al., 2015). Furthermore, assessing the impact of an intervention making use of marginal conversion factors can lead to higher CO_2 savings and lower primary energy (PE) use, with estimated deviations found by Hamels et al. (2021) of about 30%. The importance of this work lies in the role that PEFs and EFs play in the context of the European energy transition and the associated policy goals with respect to reducing the EU's primary energy use and CO_2 emissions associated to electricity.

The variability in grid performance assessments is achieved through the application of methodological aspects studied in literature. As Cubí et al. (2015) found, applying hourly temporal resolution (rather than yearly) into building assessment methods lead to environmental and energy use benefits, with differences that are not only for the sake of accuracy in and of itself, they can also affect comparisons between the merits of different technologies. Hamels et al. (2021) also found accuracy improvements up to 6%. Additionally, incorporating marginal rates to assess the impact of an intervention also accounts for how specific generators respond to system demand changes, and it is the emissions intensity and PE use of these generators that dictates the actual benefits brought about. The study carried out by Hawkes (2010) demonstrates the need of assessing the marginal grid performance at a national scale, observing the proportion of marginal differences and estimating the significance of interventions compared to a system average rate.

Assessing the grid performance at a national scale requires additional methodological aspects mentioned in literature such as the multi-regional input-output models (Hamels et al., 2021), the life-cycle perspective (Tranberg et al. 2019) and accounting electricity imports from bidding zones considering country-specific conversion factors (CFs). The benefits of these aspects lie in coherent comparisons between PE and CO_2 emissions results. A methodology aspect to investigate is the evaluation of considering hydro plants for the development of models representing how the grid is running. While renewable sources such as wind or sun are not controllable, hydro power is controllable to some extent for the penalty signals development.

This work focuses on the impact of hourly conversion factors and marginal values. The robustness of a methodology to design marginal penalty signals (marginal emissions and marginal non-renewable primary energy factor) based on historic values and having consumption load and share of renewables as parameters is tested. Demand response strategies as activated by the marginal emissions factor (MEF) or marginal primary energy factor (MPEF) signals can be used to reduce the carbon footprint and PE use of the built environment (Pean et al., 2018).

2. Objectives

This paper explains the generation method of penalty signals based on marginal variables of the electrical grid (marginal emission and marginal non-renewable primary energy factor) based on real values and a simplified method based on system load and share of renewables. It aims at testing a methodology that highlights hourly and marginal variability of the grid performance in the building assessment methods. By applying these signals to series of periods, potential differences are investigated in significant high emissions or pandemic period subsets. It focuses on the impact of accounting for the variable performance of the electric grid incorporating a robust methodology for accurate assessment of how the electricity generation performs in the Spanish context. Results are compared with average outcomes so the potential of marginal values can be observed to activate flexibility due to its variability.

3. Methods

The methodology explained in this section can be directly used to compute the hourly marginal factors associated to a period of time. It can be applied to obtain both the grid emissions or primary energy factors with hourly variability. Due to this time-based nature, it serves as a procedure to develop time-dependent strategies of electricity use for primary energy assessments and CO_2 emissions mitigation.

3.1 Calculation of hourly marginal factors

The steps followed for this calculation were:

- Retrieve data about electricity generation processes and build final dataset.
- Computation of the renewables ratio for the different periods considering hydro plants or not.
- Calculation of average factors.
- Calculation of marginal factors.

These different steps are detailed hereafter.

- Dataset elaboration

A unique source (Red Electrica de España 2021) was considered for this analysis. Data was retrieved from the Spanish Transmission System Operator (TSO) through the ESIOS website. The temporal scope considered range from January 1st, 2016 to 31st December, 2021. The data consists of hourly energy net generation[1] for the national grid per technology. The final dataset was obtained following the next computations:

1. Data was retrieved for every year. The final dataset consists of 52k data points per variable (indicator) considered: electricity generation for 20 technologies, the interconnections exchanges (imports and exports) for the 4 bidding zones, pumping consumption, Balearic HVDC link and grid losses (transport and distribution).
2. Energy generation was mapped per renewables (see Table 1). Renewable technologies include wind, photovoltaic, solar thermal, ocean/geothermal, biomass, biogas, waste, hydropower and pumped hydro. Non-renewable sources include nuclear, coal, combined gas cycle, natural gas cogeneration and fuel. Inside of these groups, energy generation was previously aggregated per generation type. For instance, fuel includes fuel, fossil oil and mining; coal includes soft coal and coal; waste includes household and sundry waste.
3. The energy balance between consumption and generation was computed. The generation demand is shown in (1) Eq. and the consumption demand in Eq. (2), where $D_{b.c.}$ is generation demand; $E_{b.c.}$ is the sum of the renewables (G_r), non-renewables (G_{nr}), turbine consumption (C_{tb}) and balearic link (B_l); Interconnections exchange is represented by I_e, consumption demand by DC and L are the grid losses:

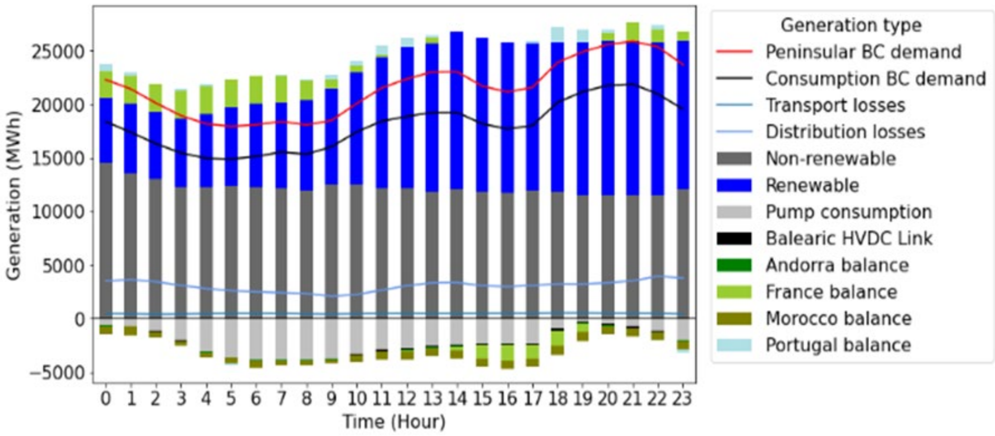
$$D_{b.c.} = E_{b.c.} + I_e = G_r + G_{nr} - C_{tb} - B_l + I_e \quad (1)$$

$$DC = D_{b.c.} - L \quad (2)$$

[1] At this state, power plants have deducted their own energy consumption (ESIOS, 2015).

An example of the data available is presented with the electric balance over the 1st of January (2016) in Figure 1:

Figure 1: Electric balance over 01/01/2016.



- Computation of the renewables ratio

The ratio of renewables for every year is computed considering or not hydro plants. This distinction is made because hydro is controllable to some extent, while sun and wind are not controllable. RES – E ratio measures the contribution of electricity produced from renewables to the national electricity consumption. It comprises the generation from renewable plants (excluding pumping) (Eurostat, 2008). The ratio of renewables is computed as shown in Eq. (3) and (4), where $\sum G_r$ is the generation from renewables and $\sum G_{nr}$ from non-renewables:

$$\text{RES-E} = \frac{\sum G_r}{\sum G_r + \sum G_{nr}} \tag{3}$$

$$\text{RES-E}_{\text{nohydro}} = \frac{\sum G_{\text{r-nohydro}}}{\sum G_{\text{r-nohydro}} + \sum G_{\text{nr-nohydro}}} \tag{4}$$

- Calculation of average factors

Technology-specific conversion factors were used for the assessment, retrieved from different sources (see Table 1), enabling to convert the generated energy into CO_2 emissions or primary energy. They are used to compute the average factors per hour as shown in (5) and (6) Eq., where DC is the total generation from the set of the 20 sources listed in Table 1 (renewable, non-renewable, imports and Balearic link). Each generation source *s* at hour *h* [units in MW*h*] in this set is represented by $E_{b.c._{s/h}}$ .The energy generated by all sources at hour h (computed before), units in [MW*h*] is represented by DC_h. The CO_2 emission factor of sources EF_s^{CO2} , units in [kgCO_2/kWh]. The primary energy factor of sources PEF_s, units in [kWh_pe/kWh].

The CO_2 emission factor at hour h, units in [kgCO_2/kWh] is defined as:

$$\text{EF}_\text{h}^\text{CO2} = \frac{\sum(\text{E}_{\text{b.c.}_{\text{s/h}}}) \times \text{EF}_\text{s}^\text{CO2}}{\text{DC}_\text{h}} \tag{5}$$

The primary energy factor at hour h, units in [kWh_pe/kWh] is defined as:

$$\text{PEF}_\text{h} = \frac{\sum(\text{E}_{\text{b.c.}_{\text{s/h}}}) \times \text{PEF}_\text{s}}{\text{DC}_\text{h}} \tag{6}$$

Table 1. Conversion factors.

		EF_s^{CO2} [kgCO2/kWh]		PEF_s [kWh_pe/kWh]	
		Value	Source	Value	Source
Non-Renewable	Nuclear	0.012	[1]	3.030	[5]
	Coal	1.210	[1]	2.790	[5]
	Combined Gas Cycle	0.492	[1]	1.970	[5]
	Natural Gas Cogeneration	0.380	[2]	1.860	[5]
	Fuel	0.866	[1]	2.540	[5]
Renewable	Wind	0.014	[1]	0.030	[6]
	Photovoltaic	0.071	[1]	0.250	[6]
	Solar Thermal	0.027	[3]	0.030	[6]
	Ocean/Geothermal	0.082	[1]	0.078	[7]
	Biomass	0.054	[1]	1.473	[5]
	Biogas	0.018	[4]	2.790	[5]
	Waste RSU	0.240	[2]	1.473	[5]
	Hydro UGH (reservoir)	0.024	[1]	0.100	[5]
	Hydro non UGH (run-of river)	0.004	[1]	0.100	[5]
	Pumped Hydro/storage	0.062	[1]	1.690	[7]
Imports	France	0.068	[1]	2.553	[1]
	Portugal	0.484	[1]	1.587	[1]
	Morocco	0.729	[1]	2.200	[1]

Note: EF_s^{CO2} represents the CO_2eq CF and PEF_s the non-renewable PE CF. Annual (constant) average values. References: [1] (Tranberg et al. 2019), [2] (Esios REE, 2021), [3] (IPCC Annex III, 2014), [4] (IPCC Annex II, 2014), [5] (IDAE, 2014), [6] (EU, 2015), [7] (IPCC, 2011).

- Computation of marginal factors

The marginal emissions or marginal primary energy correspond to the quantity of CO_2 emissions or primary energy which are avoided for every kWh of electricity saved at a certain moment. It highly depends on the national context and the energy mix of a country (Hawkes, 2010). Therefore, to compute the overall average marginal factors (MEF and MPEF) for a concrete period in the Spanish context, two time series were calculated: the difference in the system load ($\Delta\mathrm{DC}$) and the difference in the average CO_2 emissions ($\Delta\mathrm{E}^{CO2}$) or the difference in the average primary energy use ($\Delta\mathrm{PE}$), from one hour to the next, computed as shown in Eq. (7), (8) and (9):

$$\Delta DC = DC_h - DC_{h-1} \tag{7}$$

$$\Delta E^{CO2} = DC_h \times EF_h^{CO2} - DC_{h-1} \times EF_{h-1}^{CO2} \tag{8}$$

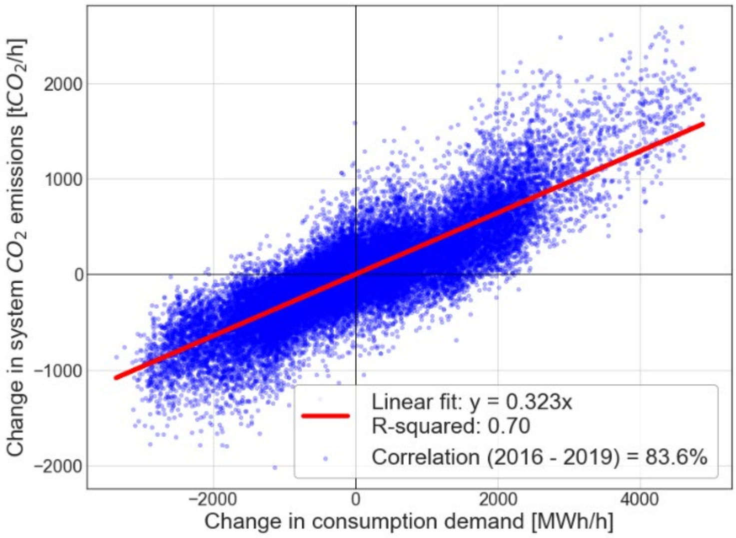
$$\Delta PE = DC_h \times PEF_h - DC_{h-1} \times PEF_{h-1} \tag{9}$$

The time series from (7), (8) and (9) equations are analyzed with a graphical analysis and a correlation test to determine the existing relationship (see Figure 2). Since the relationship is linear, a model using the linear regression algorithm is used as shown in (10) and (11) Eq. From these equations, it can be obtained the overall average marginal factors, which corresponds to the slope of the linear regression β_1, the coefficient that estimates the CO_2 intensity and primary energy use change corresponding to a demand change:

$$\Delta E^{CO2} = \beta_{E_1} \Delta DC \tag{10}$$

$$\Delta PE = \beta_{PE_1} \Delta DC \tag{11}$$

Figure 2: Scatter plot and regression line representing the 2016 – 2019 period.

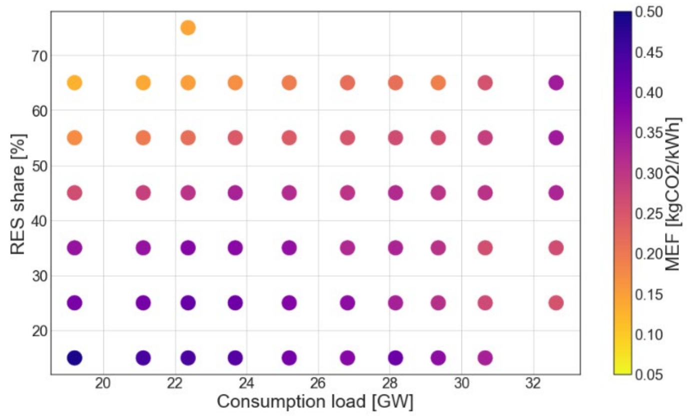


The strenght of the relationship between these variables is assessed with the Pearson coefficient of correlation (r) (value of 83.6% in the example of Figure 2). The coefficient of determination (R^2) (value of 0.70 in the present example) is used as the measure relevaling how the data points are scattered around the regression line, showing that the model could account for a better amount of variance. Disperse data points might be explained by the influence of seasonality, proportion of RES, hourly variations and presence of outliers, which is studied in section 3.2 (MEF and PEF models as function of RES share and system load).

3.2 MEF and PEF models as function of RES share and system load

To obtain better estimations of the marginal rates (account for a better amount of variance assuming high correlation) data are clustered per load and proportion of RES. Data points in Figure 3 are mapped according to the ascending system load into groups of same number of data points. Inside of these equal-sized datasets, the data is then mapped per proportion of RES (hydro and non-hydro). For each final segment of data, a linear regression is realized to obtain the MEF and MPEF. The correlation coefficient (r) of each prediction is calculated and the coefficient of determination (R^2) to decide if the linear regression results are considered reliable.

Figure 3: MEF calculated per clusters of RES share and system load (data from 2016 to 2019).

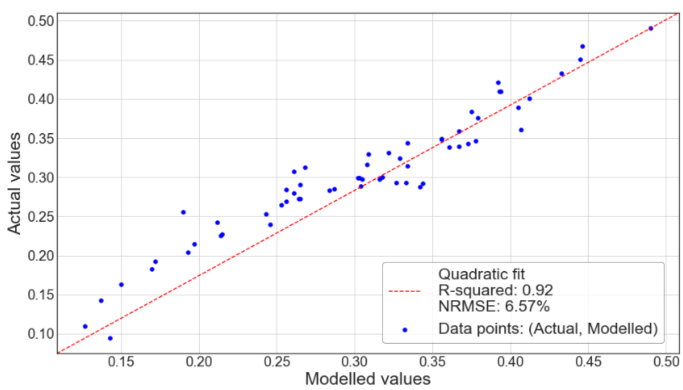


Clusters of data show a high correlation between the independent variables (MEF and MPEF) and the dependent variables (load and RES share). The coefficient of determination of each cluster (R^2) reveals higher values that the ones obtained in the dataset without clusterization. Results are considered reliable, thus the linear model can then be applied to different subsets (periods) of the segmented dataset as shown in Figure 3, which demonstrates the dependency of MEF with the system load and proportion of RES. Using a quadratic regression instead can be better used to predict MEF and MPEF due to the nature of this relationship. Regression models appear hereafter in (12) and (13) Eq.:

$$MEF \;= \alpha_{E_0} + \alpha_{E_1} R \;+ \alpha_{E_2} L \;+\; \alpha_{E_3} R^2 \;+\; \alpha_{E_4} L^2 \;+\; \alpha_{E_5} R \cdot L + \in \tag{12}$$

$$MPEF \;= \alpha_{PE_0} \;+\; \alpha_{PE_1} R \;+ \alpha_{PE_2} L \;+\; \alpha_{PE_3} R^2 \;+\; \alpha_{PE_4} L^2 \;+\; \alpha_{PE_5} R \cdot L + \in \tag{13}$$

Figure 4: Quadratic fit of the MEF function of the RES share (with hydro) and system load.



From the models, alpha coefficients can be deduced to convert the regression into a predictive function to return predicted MEF and MPEF values based on the consumption load and a proportion of RES. The values obtained for the coefficient of determination (R^2) (value of 0.92 in the present example) and the mean square error (MSE) represented in Figure 4 with its normalized value (NRMSE) (value of 6.57% in the present example), indicate that our model is reasonably accurate in its predictions. Then, the methodology can be directly used to analyze a particular period of time by applying (12) and (13) equations to the time series of the power grid. Therefore, the construction of these signals can serve to develop time-dependent strategies of electricity use for CO_2 emissions mitigation and primary energy optimization.

3.3 Analysis periods

The methodology explained in the section 3.2. can be applied to complete year data sets or to time series which are subset of data in a year or a set of data including several years. After initial analysis of the available data, the methodology has been applied to group of years data sets: years (2016 – 2019), years in the pandemic period (2020-2021) and full period (2016 – 2021). The selected periods for the pandemic COVID-19 have been split from March 14th to June 20th, being defined based in the circumstances related to the Spanish context. Thus, the periods that describe the pandemic in Spain are:

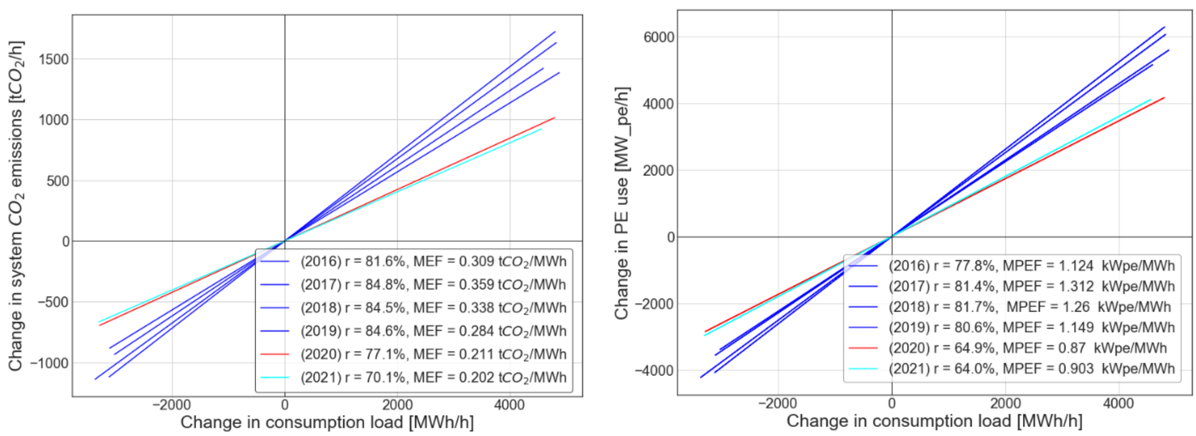
- Lockdown or strict confinement (March 14th to May 4th).
- Reopening or variable restrictions (May 4th to June 20th).
- New normal or absence of restrictions (June 20th onwards).

4. Results

4.1 Marginal factors

The summarized results of the overall CO_2 intensity of a demand change (MEF) and PE use of a demand change (MPEF) are presented in Figure 5. Robustness of the methodologies is measured by the average year correlation being about 80% for historical presented in blue, whereas pandemic, years 2020 and 2021 (red and cyan) reached about an average of 65% for both marginal estimations.

Figure 5: Average MEF and MPEF for the years 2016 to 2021.



CO_2 emissions factor results show similar behaviour of the MEF over historical (2016 – 2019), whilst a considerable reduction in marginal emissions is observed in the COVID-19 years. For instance, the year of 2021 saw its marginal emissions reduced in 44% (value of 0.202 tCO_2/MWh) compared with the value obtained in 2017 (0.359 tCO_2/MWh). Results for the Non-renewable primary energy factor indicate similar behaviour of the MPEF over historical (same as MEF). Both show a considerable reduction in MPEF of the electric grid, where 2020 shows the largest reduction with a MPEF value of 0.87 kW_pe/MWh. Comparing with the value for 2017 of 1.312 kW_pe/MWh, pandemic caused a reduction of the marginal primary energy use of about 35%. Figure 5 demonstrates differences between complete years. Data is aggregated per periods with similar trends and results for the average and marginal factors are presented in Table 2.

Table 2. Results for the historical, pandemic and all the years.

Period	AEF [tCO_2/MWh] AEF_p^{CO2}	MEF [tCO_2/MWh] MEF_p^{CO2}	APEF [kWh_pe/kWh] $APEF_p$	MPEF [kWh_pe/kWh] $MPEF_p$	RES-E (hydro) [%]	RES-E (No hydro) [%]
2016-2019	0.276	0.321	1.973	1.211	37.60	26.69
2020-2021	0.170	0.193	1.711	0.886	46.90	34.74
2016-2021	0.241	0.281	1.886	1.108	40.70	29.38
Strict lockdown	0.143	0.097	1.810	0.679	48.39	32.01
Reopening	0.167	0.124	1.619	0.644	48.99	34.43
New normal	0.180	0.222	1.801	0.886	43.95	33.78
Building code	0.331	-	1.954	-	-	-

Note: Building code refers to the values used in building assessment codes (source: IDAE, 2014).

Results reveal the differences observed in Figure 5, where pandemic period saw reduced both its emissions and primary energy. These differences in pandemic subsets are presented in the second part of Table 2 to better observe the effects of COVID-19, where the MEF in the pandemic period reached lower value (0.097 tCO2/MWh) than the average EF (0.143 tCO2/MWh), while for most of the other periods, in particular pre-pandemic, the MEF was higher than the AEF. This can be explained in part by the low demand of this specific period, and the fact that the proportion of RES was already high, hence a further reduction of the demand would not induce a major additional reduction of the emissions. MPEF values are notably lower in the pandemic subsets, where they are reduced by about 40% regarding to APEF values. For instance, the strict lockdown sees its average PEF in 1.810 kWh_pe/kWh whilst the MPEF is 0.679 kWh_pe/kWh. Additionally, the value used in building assessment codes (IDAE, 2014) as the system average emissions rate of 0.331 tCO2/MWh and the system average primary energy rate of 1.954 kWh_pe/kWh. Those standard values are higher than the calculated values in this study, although they are closer to the calculated values of the pre-pandemic period. This justifies the use of hourly average rates, technology and country-specific factors that can lead to a very different view of the significance of interventions than the system average rate.

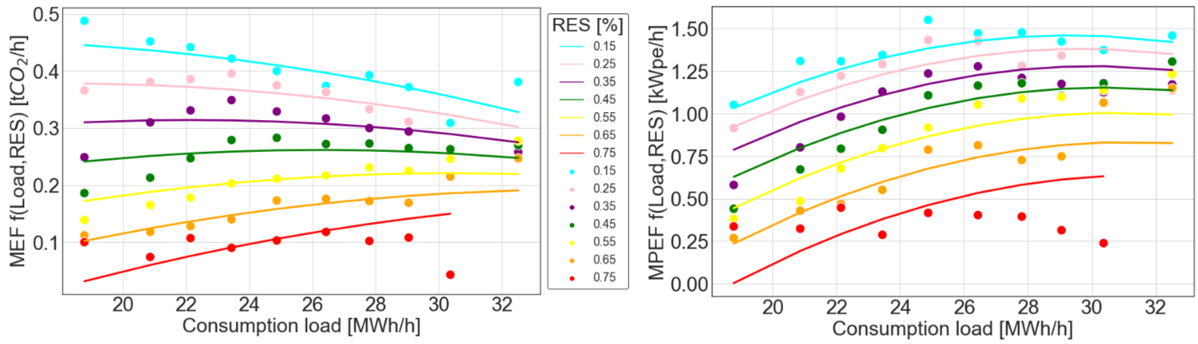
4.2 Models

MEF and MPEF models dependent on system load and share of renewables are fitted by minimizing the mean square error (MSE). The method was tested for the three main periods (historical, pandemic and full period), and with the two different RES calculations (with or without hydro). Table 3 presents the results for the quadratic regression, while the comparison between the MEF and MPEF models and the data points for the period 2016 – 2021 is presented graphically in Figure 6.

For the marginal CO2 emissions factor (MEF), the best model appears in the full period 2016 – 2021, with a R^2 value of 92.3 % (hydro) and 87.7 % (no hydro), where the value of RMSE is 0.029 kgCO2/kWh or normalized value NRMSE = 6.51% (hydro) whereas RMSE is 0.031 kgCO2/kWh or normalized value NRMSE = 7.2% (no hydro). Despite the good fit, Figure 6 reveals that in the cases of very high RES percentage (75%) and high load (>30GW), the model performs worse, with a data point diverging from the model. In terms of MPEF, notable differences appear for the full period of years and the pandemic period with a difference in NRMSE, reaching a lower value for the model considering hydro with a difference about 4%.

Similarly to the emissions, MPEF in cases of high RES and high load, the model tends to preform worse, with several points diverging from the line of the model.

Figure 6: Quadratic model (lines) of the MEF and MPEF functions of the RES share (with hydro) and consumption load.



The analysis concludes a good accuracy of the models, whereas those including hydro in their share of renewables present better fit yielding higher coefficient of determination (R^2) and reaching lower values of NRMSE. For this reason, the chosen model for the remainder of the analysis is the one fitted using data of the whole period 2016-2021 and with the RES including hydro.

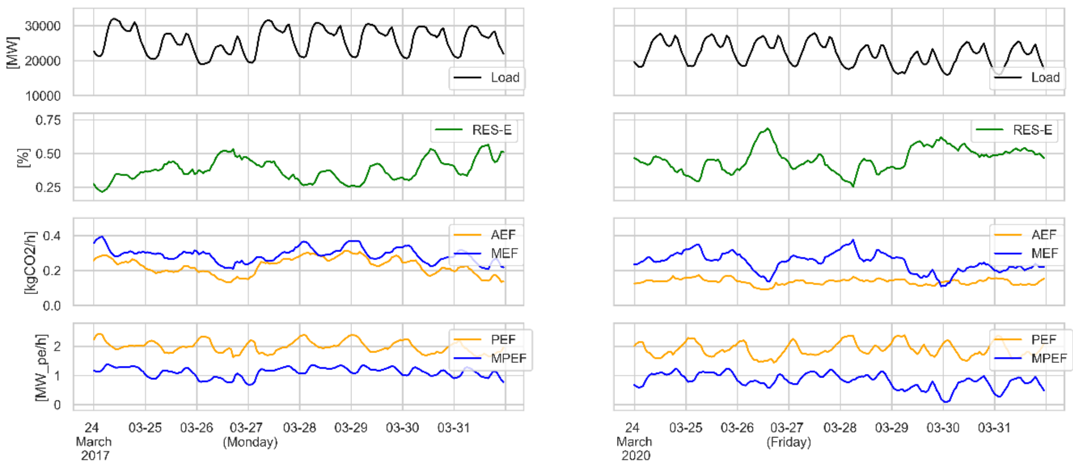
Table 3. Results for the quadratic regression for the different periods.

		MEF			MPEF		
Period	RES type	R^2 [%]	NRSME [%]	RMSE [%]	R^2 [%]	NRSME [%]	RMSE [%]
2016 – 2021	Hydro	0.923	0.065	0.029	0.875	0.139	0.133
	No hydro	0.877	0.072	0.031	0.848	0.172	0.142
2016 – 2019	Hydro	0.919	0.066	0.024	0.857	0.102	0.113
	No hydro	0.860	0.096	0.024	0.810	0.120	0.123
2020 – 2021	Hydro	0.874	0.083	0.026	0.865	0.160	0.122
	No hydro	0.820	0.087	0.029	0.834	0.202	0.139

4.3 Penalty signals

Signals to activate energy flexibility are presented in Figure 7 as an example of application of the method. They are generated for a few days of the same period of the year (March 20th – March 31st) which corresponds to the period of strict lockdown, seeking for differences between the pandemic (2020) and the year that experienced higher emissions (2017). Deducted alpha coefficients from the chosen model (2016-2021) are used to convert the regression into a predictive function to return predicted MEF and MPEF values. To interpret the results, low values of MEF and MPEF corresponds to a favourable case to use electricity, the related CO_2 emissions and PE use of non-renewable technologies will be lower. High MEF will trigger higher emissions. If MPEF high, it will result in a higher energy use of non-renewable technologies.

Figure 7. Time series for several days of March in 2017 and 2020 (strict lockdown).

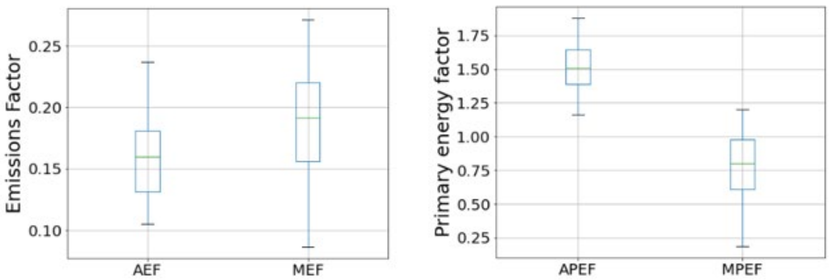


Results from Figure 7 show how MEF better captures the variability of the electric grid (rather than average). The trend remains the same whilst the amplitude of MEF curve is larger. The dynamic behaviour of the marginal emissions signal offers an amplitude that could result in larger CO2 reductions when used as input for energy flexibility strategies. On the other hand, the MPEF signal presents a similar level of variations as its corresponding average signal, although it takes in general lower values. As mentioned in section 4.2., the model to compute this signal do not account for variations when the proportion of RES and load are high. It is observed that the average and marginal PEF have in general opposite behaviour: one increases while the other decreases. As a consequence, using one or the other signal would incite to use energy at different times of the days. For this reason, it is considered preferable to use the marginal signal, as it would give the most correct estimation of the effect of a load change in terms of primary energy, after activating an energy flexibility strategy. Figure 7 also demonstrates the effect of the pandemic period with its penalty signals taking lower values: higher proportion of RES (lower consumption load associated) and a lower average EF is observed, whether the marginal emissions appear slightly lower showing more variability.

4.4 Impact of marginal rates

To better exemplify graphically these variations, Figure 8 represents the distribution for the average EF and PEF and marginal rates (MEF, MPEF) for a few days of 2016. This figure shows marginal values reaching higher variability than AEF values. This largest amplitude leaves room for optimization in the application of demand response strategies to activate flexibility in buildings.

Figure 8: Distribution of emissions and primary energy factors for marginal and average rates.



5. Conclusions

Higher temporal rates (hourly than yearly) can help to better assess the grid performance. A methodology to compute the hourly factors associated to different years and specific periods of time offers a roadmap to develop time-dependent strategies of electricity use for primary energy assessments and CO_2 emissions mitigation. If one were to make use of yearly values from building assessment codes, the final estimations would be overestimated. Thus, the use of hourly average rates, additionally taking into account technology and country-specific factors can lead to a very different view of the significance of interventions than using the system average rate.

The importance of this work lies in the important role that PEFs and EFs play in the context of the European energy transition and the associated policy goals with respect to reducing the EU's primary energy use and CO_2 emissions associated to electricity. The better these conversion factors capture the variability of the grid, the more they help to track progress towards the policy goals, and they enable, as Hamels (2021) pointed out, comparisons between different technologies and measures that can play a role in reaching them. As the system continue to be electrified, the importance of these conversion factors will only increase in the coming decades. This assessment presents limitations. The primary energy use of the grid is only assessed through non-renewable CFs, thus the same computation might be applied to assess the total primary energy by using total PE CFs.

The development of a quadratic model is studied through this work so the marginal variability can be better explained. Disperse data points might be explained by the influence of seasonality, proportion of RES, hourly variations and the presence of outliers. A study carried out segmented the marginal rates in function of the proportion of RES and consumption load, allowing to identify the dependency of the MEF and MPEF with the RES share and consumption load. By applying the quadratic regression due to the nature of these data points, a model that represents the variability of the data in more than the 90% on its predictions accuracy is then formulated and can be applied to subsets of periods to generate penalty signals for CO_2 savings and PE reduction.

This paper therefore reflects the procedure to generate penalty signals based on marginal values. Assessing the impact of demand side interventions making use of marginal conversion factors can lead to higher CO_2 savings and lower PE due to the higher variability that they offer (rather than average values). Marginal factors as dynamic signals can then be used as an input to activate the energy flexibility of heat pumps or other electricity loads in buildings (Péan et al. 2018).

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