Environmental and Economic Impact of Demand Response Strategies for Energy Flexible Buildings

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Abstract
The present work develops research to exploit the energy flexibility of buildings through rule-based controls. A novel signal representing the marginal CO2 emissions of the electricity grid is created, and its calculation methodology detailed, so that it can be applied to other energy systems. This signal is used as an input by a rule-based controller acting on the indoor temperature set-point of a residential building equipped with a heat pump. Through this set-point modulation, the energy use of the heat pump is displaced towards periods of lower CO2 intensity. A similar method is applied with an electricity price signal, and both strategies are compared in terms of energy, CO2 emissions and monetary costs. The two rule-based controls perform in a relatively similar way in the heating season (although with improvements of different amplitudes), while especially the price-based modulation produces adverse effects in the cooling season.

Introduction
The present work aims at comparing the impact of different rule-based control strategies which exploit the energy flexibility of thermal loads in buildings equipped with heat pumps. By shifting these thermal loads to periods where the CO2 emissions or energy prices of the national electricity grid are lower, the emissions or the electricity costs can be respectively reduced.

Smart controls are needed to implement these actions. The paper thus proposes a method to design such control strategy, in the form of a rule-based controller reacting on a signal based on CO2 emissions, and compare it with a similar strategy reacting to an electricity price signal. The impacts in terms of energy use, CO2 emissions, energy costs and thermal comfort of the occupants are evaluated, to assess the overall performance of the designed strategies.

Energy flexibility in buildings has been extensively studied in recent years; however a majority of the literature resorted to economic optimizations in order to reduce the energy costs (Masy et al. 2015, Schibuola et al. 2015, Le Dréau and Heiselberg 2016, Péan et al. 2017a). In such cases, the impacts in terms of CO2 emissions or primary energy are usually calculated with average values. The novelty of this work is double: firstly, its approach intends to reduce the impact of the building energy use by directly decreasing its CO2 emissions. Furthermore, the marginal emissions factor (MEF) has been used, which provides a more accurate calculation of the CO2 emissions savings due to demand-side management interventions. The method is validated through the present paper, and the calculation of the MEF for the Spanish case can be reused for later studies. Secondly, the impact of a CO2 based strategy is compared against a traditional cost reduction based strategy that was previously developed and tuned (Péan et al. 2017a, 2017b), considering the dynamics of prices, primary energy and CO2 emissions of the energy mix.

Methods
Design of marginal CO2 emissions signal
In order to reduce the CO2 emissions, a signal of the marginal emissions factor (MEF) at national scale in Spain is used by the controller. The marginal emissions correspond to the quantity of CO2 emissions 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).

To calculate the MEF for the Spanish case, the following steps have been followed: firstly, the hourly data of the energy mix have been retrieved from the Transmission System Operator (TSO) (Red Electrica de España 2018). The data contains the breakdown of the electricity production for every hour, detailed per energy source. Considering the CO2 emission coefficients of each energy source (IPCC Working Group III 2014)1, the average CO2 emission factor (EF, in kgCO2/kWh) can be computed for every hour of the year. Secondly, two time series are calculated: the difference in the system load and the difference in the average CO2 emissions, from one data point to the next. These data are represented as a scatter plot in Figure 1.

From this figure, the overall MEF can be derived: it corresponds to the slope of the linear regression, here 0.238 kgCO2/kWh (for comparison, the average MEF found by (Hawkes 2010) for Great Britain was 0.69 kgCO2/kWh). However, it is observed in Figure 1 that the

1 NB: the emissions of the electricity imported/exported with the neighbouring countries were not considered, as the overall CO2 emission of these countries was not available. It is believed this would only have a limited impact on the results.
data points are relatively scattered. In fact, the MEF varies substantially at different scales, both seasonally and according to the system load, the time of the day or the proportion of renewable energy sources (RES) in the energy mix. For this reason, the data points of Figure 1 have been clustered according to the following rules:

- First, the data are clustered per ascending system load, into 10 clusters of equal size (same number of data points),
- Inside these 10 datasets, the data are then clustered per proportion of RES (from 10% to 70% and with steps of 10%), with at least 50 points.
- For the data points of each obtained cluster, a linear regression similar to the one presented in Figure 1 is realized, to obtain the MEF of the cluster.

The resulting MEF values are plotted in Figure 2 with colour mapping, in function of both the average system load and the RES share of the clusters. These MEF values have been obtained with an average correlation coefficient of 76% in the different clusters, thus the linear regression results are considered reliable.

Figure 2 clearly demonstrates the dependency of the CO₂ MEF with the RES share and the national load. When both the RES and the load are low, the MEF reaches higher values, because the remaining base load must be covered with CO₂ emitting sources. At middle load levels and high RES share, the MEF displays its lowest values: at these points, there is enough margin to increase the load and benefit from the high availability of renewable sources. Finally, when the load is high, the dependency of the MEF on the RES share tends to disappear.

To obtain a more direct expression of the MEF, a quadratic fit is derived from the data points presented in Figure 2. The equation of this model is shown in (1), with $L$ the system load (GW), $R$ the RES share (%) and $a_i$ the fitting coefficients. The comparison between the model and the data points is represented in Figure 3. The model is fitted by minimizing the root mean square error (RMSE), which reaches the value of $RMSE = 0.00062 \ kgCO2/kWh$ or as a normalized value: $NRMSE = 0.28\%$.

\[
MEF = a_0 + a_1R + a_2R^2 + a_3L^2 + a_4R \cdot L
\]

When analysing a particular period of time, the MEF can then be obtained by applying (1) to the time series of the power grid. An example is represented in Figure 4: the system load (a) and the RES share (b), enable to calculate the MEF (d) thanks to the quadratic fit equation. The MEF and the average EF curves (compared in Figure 4 (d)) globally follow the same trends. However, the MEF displays variations of larger amplitude than the average EF, and therefore leaves more room for optimization, which is the main reason behind the whole MEF signal calculation.

To interpret the curves, it should be reminded that a low MEF corresponds to a favourable case to use electricity (the related CO₂ emissions will be lower), while a high
MEF will trigger higher emissions. The MEF signal and the price signal (traditionally used as an input signal for load-shifting) show a rather similar behaviour, although the price signal (PVPC = Precio Voluntario para el Pequeño Consumidor, or voluntary price for small consumers) has a clear day/night discrepancy by construction. It should be noted that for instance, the MEF signal shows a clear valley around midday, which is also present, but less evident in the PVPC signal. This situation is foreseen to amplify in the future: in (Klein et al. 2016), the authors have analysed the energy mix of Spain in 2030 and deduced that it will be more profitable to use energy during day hours for a grid-optimal scenario (i.e. when the residual load is negative, due to the importance of solar-based energy).

These statements are highly dependent on the country (see observed differences between Spain and Great Britain for the average MEF), the energy mix, and the dispatching of the energy sources within the grid. The operation of the grid also influences greatly the MEF calculation: for instance, it seems from Figure 4 that mainly hydropower and gas are used to absorb the daily load fluctuations, while another management strategy would probably lead to different results in terms of marginal emissions.

**Hourly electricity price signal**

The electricity price signal is retrieved from the information system of the Spanish TSO (Red Electrica de España 2018). In Spain, variable hourly tariffs (PVPC) are already applied to small consumers with a contracted power of less than 10 kW. The PVPC tariff with 2 periods varies hourly but still presents in general a higher price during the daytime (from 11:00 to 21:00 approximately) and a lower price during the rest of the day. With the current rollout or smart meters, it is assumed that the end-consumer has or will have in the near future a direct access to the variable prices (the prices are usually sent at 22:00 for the next day). An example of PVPC is shown on Figure 4 (c).

**Building study case and model**

The control strategies are tested on a residential building study case. It consists of a flat of 109 m² in a multi-storey apartment block, designed for a family of 4 members. A system of Fan-Coil Units (FCU) installed in every room conditions the space, both for heating and cooling. The FCU circuit is supplied by a reversible air-to-water heat pump of nominal thermal heating power 4.3 kW. The detailed building model was created in TRNSYS and validated by comparison with metered data (Ortiz et al. 2014, 2016). The reference indoor temperature set-point is 20°C during occupancy time and 18°C otherwise in heating mode; 25°C and 28 °C respectively in cooling mode.

$$T_{\text{ref}} = \begin{cases} 20^\circ \text{C} & (\text{occ. }), 18^\circ \text{C otherwise (heating)} \\ 25^\circ \text{C} & (\text{occ. }), 28^\circ \text{C otherwise (cooling)} \end{cases}$$

**Control strategy and simulations**

Both the aforementioned MEF and PVPC price signals are used as inputs for the DSM control strategy. For commodity and generalization purpose, we now refer to them as “penalty signal”.

Thresholds are calculated hourly on the penalty signal, both for high and low penalty. When these thresholds are passed, the reference set-point is modulated with an amplitude of $\Delta T_{\text{SP}} = 1^\circ \text{C}$, according to the following equations:

$$T_{\text{SP}} = T_{\text{ref}} + m \cdot s \cdot \Delta T_{\text{SP}}$$

$$m = \begin{cases} 1 & \text{in low penalty periods} \\ 0 & \text{in middle penalty periods} \\ -1 & \text{in high penalty periods} \end{cases}$$

$$s = \begin{cases} 1 & \text{(heating mode)} \\ -1 & \text{(cooling mode)} \end{cases}$$

The set-point modulation expressed in (3) to (5) functions as follows in heating mode: the set-point is reduced by $m \cdot \Delta T_{\text{SP}} = -1^\circ \text{C}$ when the penalty is high, thus benefiting from this period to use energy. In cooling mode, the operation is obviously...
reversed with the switch factor \( s \), thus obtaining the desired load shifting.

The thresholds for low and high penalty are calculated as follows: the hourly penalty data of the last 24 hours is retrieved. The 40th and 60th percentiles of these points are used as the low and the high thresholds respectively. These values were obtained through parametric study in (Péan et al. 2017b).

The control strategy is tested with the two different penalty signals, both in winter and summer, through dynamic simulation using the aforementioned TRNSYS model. The list of studied cases is presented in Table 1. The entire months of February and July have been chosen as representative of the winter and summer conditions respectively in Spain.

### Table 1: List of simulated cases.

<table>
<thead>
<tr>
<th>#</th>
<th>Penalty signal</th>
<th>Heat./Cool.</th>
<th>Time frame</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Reference</td>
<td>Heating</td>
<td>February 2016</td>
</tr>
<tr>
<td>1</td>
<td>MEF</td>
<td>Heating</td>
<td>February 2016</td>
</tr>
<tr>
<td>2</td>
<td>Price</td>
<td>Heating</td>
<td>February 2016</td>
</tr>
<tr>
<td>10</td>
<td>Reference</td>
<td>Cooling</td>
<td>July 2016</td>
</tr>
<tr>
<td>11</td>
<td>MEF</td>
<td>Cooling</td>
<td>July 2016</td>
</tr>
<tr>
<td>12</td>
<td>Price</td>
<td>Cooling</td>
<td>July 2016</td>
</tr>
</tbody>
</table>

### Results

#### Results for the heating season

Table 2: Overall results of the heating cases. The values are shown for the whole month of February 2016 (absolute values for the reference case and for the other cases, variations respectively to the reference case, in absolute value and percentage).

<table>
<thead>
<tr>
<th>Case</th>
<th>0-Reference [kWh]</th>
<th>1-MEF modulation</th>
<th>2-PVPC modulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elec. use</td>
<td>251.33</td>
<td>+5.46 (+2.2%)</td>
<td>+12.70 (+5.1%)</td>
</tr>
<tr>
<td>Primary energy(^2) [kWh]</td>
<td>530.70</td>
<td>+12.09 (+2.3%)</td>
<td>+32.51 (+6.1%)</td>
</tr>
<tr>
<td>CO(_2) emissions [kgCO(_2)]</td>
<td>46.35</td>
<td>-3.93 (-8.5%)</td>
<td>-0.78 (-1.7%)</td>
</tr>
<tr>
<td>Energy cost [EUR]</td>
<td>19.98</td>
<td>-2.13 (-10.6%)</td>
<td>-4.48 (-22.4%)</td>
</tr>
</tbody>
</table>

The summarized results of the test cases for heating are presented in Table 2, and time series in Figure 5 and Figure 6. Overall, each control strategy reaches its specific goal: the MEF modulation (Case 1) enables -8.5% savings of CO\(_2\) emissions, with an additional cost decrease of -10.6%. The PVPC modulation (Case 2) enables -22.4% economical savings, and a slight decrease of the emissions of CO\(_2\) by -1.7%. The amplitude of the economic savings is greater because the PVPC signals displays larger variations and thus larger savings opportunity than the MEF signal. Both strategies result in an increase of the energy use (final or primary energy), because of the storage-like operation: thermal energy is stored in case of low penalty, to use it during high penalty periods, causing thermal losses.

It should be noted that the absolute value in the row “CO\(_2\) emissions” of Table 2 was calculated using the average EF, while the subsequent savings are calculated using the MEF. If the average EF had also been used to calculate the emissions savings, these would have been misjudged (for instance in case 1, -2.4% with the EF while the MEF gives -8.5%, and in case 2, -2.3% with the EF while the MEF gives -1.7%). It is believed that the MEF provides a more accurate representation of the CO\(_2\) savings, given that it considers the current state of the grid and the actual effects of a load increase/decrease from that state.

From the results of Table 2, it appears that the MEF modulation strategy is promising, since it leads to both economic and emissions’ savings. One could prefer the PVPC modulation strategy, given the higher cost savings provided, but its global impact on sustainability will be rather limited. In this regard, the MEF modulation offers a satisfactory balance between both objectives.

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\(^2\) The primary energy was computed with a time-varying primary energy factor, calculated itself from the dynamic breakdown of the energy mix and the primary energy factors of the different production sources.
The summarized results for the cooling season are presented in Table 3, and the time series in Figure 7. Also for these cases, each strategy reaches its claimed objective: the MEF modulation leads to -5.9% CO$_2$ emissions and a slight cost decrease of -1.8%. Furthermore, Case 11 also achieves a reduction of the primary energy use (-4.3%).

The PVPC modulation results in -20.2% cost savings, which is in the same range than in the winter case. However, Case 12 also leads to an increase in the CO$_2$ emissions of +17%, which was not observed in the heating season (where the emissions also decreased in the PVPC modulation case).

This adverse effect produced by the PVPC modulation strategy can be explained by the different configuration of the energy grid in summer. In fact, the PVPC signal keeps its day/night pattern also in summer, with high prices in the afternoon and low prices at night. Because of this high cost penalty during daytime, the heat pump use is discouraged at these hours. However, this period also corresponds to the peak of solar power production, which is more predominant in summer. As a result, the heat pump cannot make the most of this renewable source and must use electricity at times where the energy mix produces more CO$_2$ emissions, resulting in the observed increase.

Table 3: Overall results of the cooling cases. The values are shown for the whole month of July 2016 (absolute values for the reference case and for the other cases, variations respectively to the reference case, in absolute value and percentage).

<table>
<thead>
<tr>
<th>Case</th>
<th>10-Reference</th>
<th>11-MEF modulation</th>
<th>12-PVPC modulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elec. Use [kWh]</td>
<td>127.41</td>
<td>-4.70 (-3.7%)</td>
<td>15.02 (+11.8%)</td>
</tr>
<tr>
<td>Primary energy [kWh]</td>
<td>312.62</td>
<td>-13.32 (-4.3%)</td>
<td>43.74 (+14%)</td>
</tr>
<tr>
<td>CO$_2$ emissions [kgCO2]</td>
<td>34.77</td>
<td>-2.07 (-5.9%)</td>
<td>5.93 (+17%)</td>
</tr>
<tr>
<td>Energy cost [EUR]</td>
<td>11.86</td>
<td>-0.22 (-1.8%)</td>
<td>-2.40 (-20.2%)</td>
</tr>
</tbody>
</table>

Results for the cooling season

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The different behaviour between summer and winter operation is reflected in the modulation signals \( m_{\text{MEF}} \) and \( m_{\text{PVPC}} \). When comparing them for both seasons, it appears that they are equal for 49% of the time in February, revealing their relatively similar patterns (this can be observed in Figure 6 (b) and (e)). However, in July they are only equal for 16% of the time, which shows their adverse behaviours.

When selecting a control strategy for winter, one can choose either one of the two modulation strategies, knowing they will both have beneficial effects, although at different amplitudes. In summer, a clear choice must be made for the input signal between MEF and PVPC, which will determine if the focus lies on economical savings or on sustainability.

It should be stated that the implemented control strategies do not jeopardize thermal comfort. In winter, the normal set-point is 20°C during occupancy periods, which corresponds to Category II, a normal level of expectation for thermal comfort (CEN 2007). With the modulation, this set-point can go down to 19°C which is still acceptable (Category III from 18 to 20°C) or up to 21°C which corresponds to a high level of expectation (Category I). Similarly, in summer, the normal set-point is 25°C during occupancy, which is in the limits of Category I (23.5 - 25.5°C). With the modulation, the set-point can either stay within the Category I or downgrade to Category II (26°C). Changes might thus occur regarding the thermal sensation of the occupants, but an acceptable level of comfort is guaranteed.

**Discussions**

The \( \text{CO}_2 \) MEF gives indications on the level of emissions’ savings one could expect when saving 1 kWh of energy use. The calculation of the average MEF for a given energy system such as the Spanish grid is rather straightforward, as mentioned by (Hawkes 2010). However, obtaining the dynamic time-of-use variations of the MEF becomes a more complicated task. Indeed, the data points are rather scattered, as illustrated in Figure 1. Selecting the correct clusters where the MEF calculation makes more sense is thus the most challenging task.

It was observed that the MEF mainly varies with the system load and the proportion of renewable energies in the grid. The clustering was therefore realized according to these two parameters. However, other variables could be taken into account, such as the seasonal variations, the time of the day etc. In such case, more than one year of data would be necessary, so as to obtain enough data points per cluster and thus a meaningful linear regression. In particular, it was illustrated in this work that the variations between winter and summer are substantial in the Spanish energy system, so making this differentiation in the MEF calculation could be the object of further research.

The use of \( \text{CO}_2 \) emissions as an input signal to trigger the energy flexibility of buildings has been observed in several other publications, such as (West et al. 2014, Patteeuw et al. 2015, Hedegaard et al. 2017, Pedersen et al. 2017). However, these studies rely on average emissions signals, while it is believed that the marginal emissions provide a more adequate representation of the savings consequent to demand-side management actions. Furthermore, the need for dynamic signals will become even more clear given the high variability of the future energy systems, as highlighted by (Klein et al. 2017). Already in the present work, substantial seasonal differences were noted, and the amplitude of these variations will become more evident with the increasing penetration of non-dispatchable RES in the future.

It should be noted that only the most critical months have been studied: February and July, which correspond respectively to the climax of winter and summer. If one were to realize a yearly simulation implementing the proposed strategies, their effects could be mitigated by the shoulder seasons. In fact, in Spring and Autumn, the heating and cooling needs are generally smaller in Spain, and thus even the most efficient strategy has little room for savings. However, the thermal loads can also be shifted more easily due to the lower losses to the outside (milder temperatures). It is therefore expected that the control strategies still have a largely positive impact on a yearly basis.

**Conclusion**

The present work has focused on the methodology used to obtain a reliable signal of the marginal \( \text{CO}_2 \) emissions in the Spanish energy system. This dynamic signal can then be used as an input to activate the energy flexibility of heat pumps or other electricity loads in buildings. The main interests of the MEF signal resides in its variations of larger amplitude than the traditional average emission factor, hence leaving more room for optimization and demand-side management. Furthermore, the MEF provides a more realistic representation of the benefits of DSM actions, since it takes into account the current state of the grid and the normal operation of that grid (for instance the prioritization and dispatching of the energy sources in the mix).

The MEF is highly country-specific and depends also greatly on the merit order between the different sources of its energy mix. However, the methodology could be generalized and applied to other national energy systems. As an application, the MEF signal was used to activate the energy flexibility of a residential building equipped with an air-to-water heat pump. Thresholds were fixed on this time-varying signal, and a consequent indoor temperature set-point modulation was implemented. The same method was applied with a price signal, and the results were compared in terms of \( \text{CO}_2 \) emissions, final and primary energy and costs.

In the heating season, the MEF and the price modulation strategies both lead to \( \text{CO}_2 \) emissions and cost savings, obviously achieving better results in their respective declared objectives (i.e. the MEF modulation performs better in terms of \( \text{CO}_2 \) emissions reduction and the price modulation performs better for economical savings).
In the cooling season, the results provide a different reading: the MEF modulation results in a reduction of the emissions and slight decrease of the cost. The price modulation performs similarly than in winter for the cost reduction, but leads to substantially higher CO₂ emissions, which is an undesirable side effect.

Given the observed seasonal differences, and the predicted higher variability of the energy systems, the use of the MEF signal could become even more relevant in the future. An optimization framework such as model predictive control (MPC) could be utilized to benefit from such signal, and balance adequately between the economical objective and the CO₂ emissions reduction. The development of such controller is the object of further research work.

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