# How much could domestic demand response technologies reduce $CO_2$ emissions?

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## Abstract

It is standard government procedure to subject all policies, programmes and projects to comprehensive and proportionate assessments to promote the public interest and ensure best use of resources to secure national objectives. A key assessment criterion for energy efficiency policies is their expected impact on $CO_2$ emissions and, accordingly, governments require environmental impact assessments to inform decisions about which policies should be supported. As electricity systems decarbonise and progress towards higher penetrations of renewable energy, however, system balancing becomes increasingly challenging and, as a result, there is increasing value in demand response. The efficiency of low-carbon systems depends not only on policies that promote demand reduction, but also those that promote demand response.

Smart appliances are, from the grid's perspective, a means to achieve demand response and this paper is interested in the question: how much $CO_2$ do smart appliances save, in their capacity as 'demand response technologies'? This paper aims to clarify this topic by reviewing the literature on carbon savings from demand response technologies, describing a simple conceptual model that illustrates the importance of accounting for the long-run structural impact of demand response, and estimating the $CO_2$ impact for a case-study of domestic battery systems in the Irish power system. The results indicate that the carbon impact of demand response technologies may be negligible, or even negative, unless structural change in the power system occurs, such as changes to the dispatch and decommissioning of generation. This highlights the added value of the role of demand aggregators, who act as the necessary intermediary between the small-scale and distributed smart appliances and the electricity markets where their beneficial structural impacts can be most effectively enabled.

## Introduction

### *Demand-side technology changes for a low-carbon future*

Technology change is required to make energy clean, secure and affordable – the energy trilemma. The domestic sector is an area in which the required change is expected to be particularly pronounced. While there is growing concern that technology change alone may not be enough to achieve the scale and speed of emissions reduction required to keep mean global temperature rise within 2° Celsius, let alone 1.5°, above pre-industrial levels, this paper focusses on technology change in the domestic sector and in particular assessment of the effectiveness of such technologies for addressing the sustainability aspect of the energy trilemma.

### *Energy efficiency technologies and demand reduction*

Regardless of the technology change required for energy supply, reducing overall demand for energy is a critical objective. Energy efficiency technologies such as retrofit building insulation or more efficient lighting, are one of the primary means of achieving this and they are routinely assessed for their potential to reduce demand, cost effectiveness, and unintended behavioural 'rebound effects'. These assessments can provide the necessary evidence to support policy decisions about energy efficiency, make projections of future demand, and develop scenarios. Domestic appliances, for example, are regulated with the aim of improving efficiency through energy efficiency standards, and there are well-established systems of energy labelling for basic household appliances such as the EU Energy Label that help to inform consumer purchasing.

### *Smart appliances and demand response technologies*

If energy efficiency is a means to achieve demand reduction, then arguably smart appliances are a means to achieve demand response or load-shifting (Timpe, 2009). The term 'smart appliances' can be ambiguous but here refers to domestic appliances with automated demand response functionality, usually falling into the categories of wet appliances (e.g. dishwashers, washing machines, etc.), heating, ventilation and cooling technologies (e.g. heat pumps), cold appliances (e.g. refrigerators), and, in line with UK government energy policy and regulation (BEIS, 2016), includes domestic battery storage systems. Electric vehicles do not generally fall under the term, though we note that, from the grid perspective, they are similar to battery storage systems.

Demand response is defined here as a change from normal patterns of electricity demand. It includes all changes made or approved by the end-user, whether these are intended to alter the timing of demand, the level of instantaneous demand, or overall consumption (Albadi and El-Saadany, 2008). Demand response can be carried out either manually or through automation and smart appliances in response to a signal, usually a price, intended to benefit both the consumer and the wider electricity system (Darby and McKenna, 2012). For the sake of clarity, we use the term 'demand response technology' to emphasise our focus on this particular function of smart appliances. We note, though, that smart appliances are more likely to be marketed to the public on the basis of convenience and control, highlighting a potential divide between end-user and grid perceptions of 'smart'.

Demand response can have many benefits in power systems both in terms of emissions reductions and improving economics, including reduction of generation capacity, ancillary services, and more efficient use of network assets. It is often mentioned as a way of supporting the integration of renewable energy into power systems, by making the demand-side more flexible in response to an increasingly inflexible supply-side. Recently, however, there have been a number of publications estimating the environmental impact of domestic battery systems which indicate that such demand response technologies may increase emissions (Fares and Webber, 2017; McKenna et al., 2013). This paper therefore focusses on this issue and the importance of determining the environmental impact of demand response technologies.

### *Aims of the paper*

The policy goal for smart appliances as demand response technologies is the same as that for demand reduction technologies (energy efficiency): make energy more secure, more sustainable and more affordable. This paper focusses on sustainability and aims to address the question: how much could demand response technologies reduce $CO_2$ emissions?

Fundamentally we would like to know how effective different types of demand response technologies are at achieving carbon reduction and which merit support. Which have the greatest potential for reducing $CO_2$, and how do they compare alongside more traditional demand reduction technologies, that do not achieve load-shifting? Given their similar purposes, when is it more effective to invest in demand response technologies compared to those that are deployed with demand reduction in mind?

The problem is that while it is reasonably intuitive to measure a reduction in energy and translate that into a reduction in emissions, it is much less straightforward to determine the same impact when the energy has not been removed from the system but shifted to another moment in time. This paper aims to clarify this area by reviewing the literature on carbon savings from domestic demand response technologies, describing a simple conceptual model of the impact of demand response, estimating the $CO_2$ impact for a case-study of domestic battery systems in the Irish power system, and discussing the broader relevance of the findings.

## Review of the literature assessing carbon saving from demand response technologies

This section reviews a selection of the literature on environmental impact assessments of smart grid technologies, including appliances that are smart-enabled, heat pumps and battery systems. The last two are not necessarily smart – that is, they may not have two-way communications for remote control – but they are included because they are demand response technologies with the potential to be used in smart grids. There is a particular interest in the state-of-the-art in attributing carbon savings to demand response. The findings are summarised at the end of the section.

## *Smart grids*

Moretti et al. provide a recent systematic review of the environmental and economic benefits of smart grids (Moretti et al., 2016). A smart grid is a "technologically advanced network [that] is expected to facilitate the integration of renewable generation technologies such as, photovoltaics and wind, and innovative user applications (e.g., electric vehicles, heat pumps, distributed storage) into the electric grid, and thus to facilitate a transition to a low-carbon energy generation system". Demand response technologies are seen as a necessary part of a smart grid.

Moretti et al. note that there is no standard method for evaluating the economic and environmental impact of smart grids and indicate costs ranging from 0.04 to 804 M€/yr, with costs outweighing benefits on average by 59 M€/yr. Primary energy savings due to energy efficiency improvements were in the range 0.03 to 0.95 MJ/kWh, and greenhouse gas reductions in the range 10 to 180 $gCO_2$/kWh. The authors conclude that smart grids are energy efficient at the system level and likely to reduce greenhouse gases but may not yield financial benefits.

The estimates of greenhouse gas reductions given above are based on four studies, each with distinctive assumptions as to how the reductions might be achieved. Farzeneh et al. attribute savings to *more efficient technologies, micro-generation, and reducing distribution line voltages* (Farzaneh et al., 2014). Görbe et al. propose a novel power electronic controller for distributed micro-generators and estimate a 5% reduction in electricity distribution losses due to *power from distributed generation being used locally* (Görbe et al., 2012). EPRI's 'The Green Grid' report provides a first-order quantification of the energy and greenhouse gas savings of smart grids and has a specific section on energy savings from demand response programmes (EPRI, 2008). The authors *attribute the majority of greenhouse gas savings to consumers reducing energy demand due to improved information feedback about their usage, replacing internal combustion engine vehicles with plug-in electric vehicles, and greater integration of renewables*. Demand response programs are assumed to reduce peak demand by 5% and provide less than 1% of the total greenhouse gas savings. The authors note that load-shifting per se does not reduce energy demand, may increase demand in practice (e.g. pre-cooling houses), and may increase emissions if the supply-mix is more carbon-intensive during the off-peak period than the peak period. Finally, Yuan and Hu attribute greenhouse gas savings to the combined effects of *end-use energy efficiency improvements and improved efficiency of power plant from a flatter demand profile* (Yuan and Hu, 2011). In summary, in these studies the environmental benefits of smart grids are generally attributed to demand reduction from improved grid and network operations (system efficiency) and improved end-use energy efficiency. The impacts of demand response are assessed to a lesser degree, or not at all.

Darby et al. (2013) offer a framework of conditions, metrics and indicators to assess the potential for carbon savings from demand response and demand reduction. The paper first identifies potential demand-side functionalities or actions such as investment in efficiency, peak load-shifting and automated response for frequency control. It then selects indicators of regulatory and operational support for these functionalities in six contrasting EU countries and uses these indicators in wholesale and ancillary market models, in conjunction with data on supply mixes and interconnections, to estimate carbon impacts by the year 2020 under three scenarios: a base case in which there is no rollout of smart grid technology; an 'expected' scenario in which new technologies are introduced but nothing else changes; and a 'feasible' scenario that assumes legislation/regulation in support of new technologies. Each country has distinctive outcomes, ranging from 4-13% carbon savings over baseline in the best-case scenario and from 1-6% in the technology-only scenario. For all countries modelled, the biggest single driver of emission reductions is the lowering of emissions intensity due to *increased zero-carbon generation, coupled with more efficient use of fossil fuel generation through a combination of load shifting and demand reduction*. The second largest driver is 'reduction in generation volume', due to overall demand reduction. The residential sector emerges as the source of virtually all the modelled demand reduction and demand response, as it has the most regulatory support in the form of enabling programmes.

This early attempt at modelling carbon impacts from demand response explicitly takes into account static and dynamic peak-shifting and shows that both (overall) demand reduction and (time-specific) response have considerable potential for carbon savings. It illustrates the value of taking a 'power systems simulation' approach that incorporates empirical evidence on demand response along with measures of infrastructural and regulatory readiness for demand response. It also demonstrates the potential of demand response to achieve *structural* impact, as one effect of demand response within the models is to affect plant commissioning and decommissioning as a consequence of altering peak demand and generation dispatch; and the value of a system operator being able to dispatch and plan with demand response as a resource. The paper thus points the way towards a type of exercise that could support assessments of the carbon impact of smart appliances, to determine their effectiveness alongside other technologies and activities/processes.

## *Smart homes*

There is a far larger number of 'prospective' studies assessing the theoretical impact or technical potential of fully-integrated smart homes[1] than evaluative studies capable of telling us how such homes perform in practice. Evaluation of domestic smart equipment for demand response is largely restricted to programmes that involve shifting substantial cooling and heating loads in response to pricing signals e.g. (Faruqui and Sergici, 2011) – that is the programme rather than the technology itself is evaluated, and only a few end-uses are involved. There are now a few evaluations of smart thermostats, mostly with ambivalent findings at best for end-use and system efficiency e.g. (Yang and Newman, 2013). Examples of prospective studies of comprehensively smart homes (with integrated appliances, sensors and controls), are Rashidi and Cook (2009), with an emphasis on technical aspects of home automation and machine learning, and Balta-Ozkan et al. (2013), taking a more systems-based approach and including some consideration of occupant preferences and activities.

One recent evaluative and two recent prospective studies of smart homes are worth mentioning here because of their divergence from the usual optimistic narratives about their environmental impacts. Nyborg and Røpke (2013) offer a thoughtful qualitative analysis of how people respond to smart home technology, drawing attention to the need to pay attention to the co-evolution of systems and practices and potential for increased service expectations and, by implication, increased environmental impact. Louis et al. (2015) investigate the environmental impacts of smart home automation and quantify the life-cycle impact of the 'home energy management system' (HEMS) which consists of the communication devices, sensors, management devices, smart meter and computing devices that can enable smart appliances to provide automated demand response functionality as well as information feedback to the householders. Their model of a highly-instrumented smart home indicated that smart plugs (around 20 of them) consumed almost 3700 kWh smart meters nearly 880 kWh over an assumed life-cycle of five years. There were also some notable environmental impacts from the materials used in the equipment and their disposal or recycling. The net effect was that, although the smart meter 'paid for itself' in terms of carbon emissions in under a year, 'the full system does not pay itself back in terms of reduced $CO_2$ emissions' (p885) and the authors concluded that home automation might not be an environmentally sensible investment, primarily due to the impact of the smart plugs. In a follow-up study (Louis et al., 2016), the same authors extended the work to simulate smart homes under a range of operating assumptions and algorithms and found that the impact of highly automated options resulted in an increase in overall energy demand, with corresponding increases in costs and emissions. Load-shifting was considered in the study and was found to have a benefit in terms of flattening demand profiles. The authors noted the need for assessment methods that account for the temporal variations in $CO_2$ emissions of grid electricity.

## *Smart appliances*

Some appliances and end-uses lend themselves more easily than others to demand response: for a review of options, see Darby and McKenna (2012), who note that water heating and wet appliances can account for a high proportion of shiftable load at peak times. Electric space heating, as a major end-use, also lends itself to demand response, whether via the well-established storage heater or through smart-enabled heat pumps. There is also scope for fast frequency response from these end-uses and from cold appliances. While cookers may involve significant thermal loads, they are likely to have little potential for demand response for social reasons, while any other smart household appliances are likely to be smart for reasons of comfort, security or monitoring rather than for demand response purposes.

The question of scale is important when considering the relatively small loads in a typical household. As noted later, the ability to aggregate appliance loads and to realise benefits from aggregation is likely to influence householders' ability and willingness to take part in demand response; manual adjustments to their appliances in response to system conditions are not always feasible or desirable.

## *Heat pumps*

Heat pumps are a technology that is of particular interest due to the potential impact of large-scale electrification of domestic heating on peak demand and its potential as a flexible load for demand response. Hawkes developed methodologies for estimating short-run and long-run marginal emissions factors for national electricity systems, and used these to estimate the $CO_2$ impact of adding heat pumps to the UK power system (Hawkes, 2014, 2010). The short-run marginal emissions factor refers to the *change* in $CO_2$ emissions associated with a *change* in electricity demand caused by an intervention (e.g. a smart appliance) where there is little structural change in the

[1] Taking this as a definition: 'A smart home is a residence equipped with a high-tech network, linking sensors and domestic devices, appliances, and features that can be remotely monitored, accessed or controlled, and provide services that respond to the needs of its inhabitants.' (Balta-Ozkan et al., 2013).

national electricity system caused by the intervention i.e. in current or near-future conditions of supply and demand. The long-run marginal emissions factor is the same but takes into account structural changes *caused* by the intervention e.g. if the uptake of smart appliances had the effect of causing a change in what generation gets built or decommissioned. Hawkes found that the marginal emissions factors for new heat pumps were 0.67 $kgCO_2$/kWh in the short run and 0.26-0.53 $kgCO_2$/kWh by 2025 in the UK, reducing towards zero by 2035 as the power system is assumed to decarbonise. This example shows how heat pumps, as a relatively efficient form of electric heating, can already supply heating at relatively low carbon cost. The studies did not however consider the impact of demand response, and we note that if heat pumps could be used for demand response and controlled automatically in such a way as to avoid times of high demand relative to supply further gains could be made. These studies emphasise the importance of appropriate methods for accounting for interventions, such as demand response, that occur on the margin, and that therefore require estimates of marginal emissions factors, as well as the importance of accounting for both short-run and long-run effects of interventions.

Patteeuw et al. consider the $CO_2$-abatement cost of heat pumps with load-shifting in a variety of domestic building cases in Belgium in comparison to the alternative of fitting a modern gas boiler (Patteeuw et al., 2015). An integrated approach is taken, combining a bottom-up building stock model with a simulated electricity generation system. The study found a wide variation in abatement costs depending on building-type and heating system set-up, with results in the range 249-981 €/$tCO_2$ for detached buildings built between 1971-1990. A high renewables scenario was assumed and load-shifting was found to reduce emissions, in this case by avoiding curtailment of renewable energy at times of abundant supply

## *Battery systems*

Domestic battery systems are generating interest due to rapidly falling costs and their ability to allow consumers to shift demand easily. They are popularly coupled with roof-top solar panels to maximise self-consumption. Hammond and Hazeldine conducted a 'cradle-to-gate' life cycle assessment of advanced rechargeable batteries, including technical assessment for different applications, though not considering load-shifting, and found total emissions of 5.4 $kgCO_2$/kWh installed capacity for lithium-based batteries, 32.4 $kgCO_2$/kWh for ZEBRA batteries, and 88.8 $kgCO_2$/kWh for Ni-Cd (Hammond and Hazeldine, 2015). McKenna et al. (2013) assessed the economic and environmental impact of adding lead-acid batteries to dwellings with domestic PV systems in the UK and considered the effect of load-shifting on short-run marginal emissions. They found the environmental impact to be negative for all cases due to the batteries' round-trip losses and the fact that grid marginal emissions were not sufficiently different between times of charging and discharging to compensate for this. The impact of a typical battery system on the greenhouse gas emissions from an average UK household was found to be equivalent to that from increasing the household's energy consumption by 21%.

More generally, the carbon impact of electricity storage has been modelled in a number of studies that consider its effect on short-run marginal emissions, including studies of its use in support of load-shifting and where there is large-scale participation of storage in markets e.g. through aggregation of distributed resources. Mills and McGill assess the greenhouse gas impact of electric vehicle charging in Australia (Mills and MacGill, 2015), Carson and Novan assess the impact of electricity storage in the Texas power system (Carson and Novan, 2013), McKenna et al. assess the impact of storage in the Irish power system (McKenna et al., 2016), and Fares and Webber investigate the impact of using energy storage to capture solar energy for later use within the home within the Texas power system (Fares and Webber, 2017). All studies found that storage could have negative environmental impacts in the short-run and emphasised a possible tension between operating storage for private benefits e.g. increasing operator profits or householder financial gains due to arbitrage in the wholesale electricity market, and social benefits including reduced greenhouse gas emissions and greater network stability. The exception was when i) the modellers assumed that storage was used to avoid the curtailment of renewable generation, as in this specific case renewable energy operates on the margin and storage can then achieve considerable reductions in emissions compared with a counterfactual use of, say, gas turbines, and ii) if the storage enabled the installation of the solar PV system i.e. solar plus storage is better than no solar at all. However, none of these studies investigated the long-run impact of storage, in which storage is expected to play a key role in enabling structural change e.g. to achieve greater integration of renewable energy. A great deal of uncertainty surrounds the viability of different types of battery, the supply conditions in which they may have to operate, and the behavioural consequences of widespread adoption in the domestic sector.

## *Summary: towards an appropriate assessment methodology*

In summary, a review of selected literature on the emissions impact of smart technologies has revealed that

- Reported savings are often associated with improvements in energy efficiency and the potential impact of demand response is often not considered in assessments.

- Studies that take a life-cycle approach indicate that gains in appliance end-use efficiency may be reduced or offset altogether by emissions incurred elsewhere e.g. additional energy usage of associated sensors.
- Studies that do assess demand response indicate a range of possible impacts depending on the method and assumptions used. Studies based on estimates of short-run emissions factors indicate that demand response can have a negligible effect in certain power systems, or may even increase emissions e.g. due to efficiency losses in domestic battery systems.
- The extent to which demand response can avoid curtailment of renewable generation is an important factor determining its environmental impact.
- There is a need for impact assessments based on estimates of long-run marginal emissions factors, which take into account the potential beneficial impact that load-shifting could have on overall system structure.

Having set out this need for impact assessment of demand response, which could make a strong contribution to emissions reduction, the following section describes a simple conceptual model for carrying out such assessment based on data from a national power system, illustrating the significance of method and assumptions.

## Simple conceptual model for a demand response marginal emissions factor

The previous section indicated the importance of assessments that account for the long-run impact of demand response within national electricity systems. This section presents a simple model to illustrate some of the concepts involved and the types of impacts that an appropriate assessment methodology should account for. This will be based on a simple, hypothetical, and idealised power system and is not supposed to represent a particular real system. The following section will build on some of these concepts to provide an indicative impact case study of adding battery systems to the Irish power system based on real data.

The aim of the section is to calculate the demand response marginal emissions factor (DR-MEF). Conceptually, the DR-MEF is the change in emissions associated with a change in electricity demand due to a demand response intervention. We define the DR-MEF as:

$$\text{DR-MEF} = \frac{\left(\sum_{h=1}^{n}\left(E_{scenario} - E_{baseline}\right)\right)}{\left(\frac{\sum_{h=1}^{n}\left|D_{scenario} - D_{baseline}\right|}{2}\right)}$$

The variables *E* and *D* stand for emissions and electricity demand respectively. The DR-MEF is estimated for a demand response ‘scenario’ and measured with respect to the hypothetical counterfactual ‘baseline’, indicated by subscripts. The sums are at a time resolution sufficient to account for the differential effect of the demand response intervention, here hourly ($h$). The denominator is defined as the sum of the *absolute* changes in (hourly) electricity demand, as the relative change in demand associated with a (zero-sum) shift in demand is zero, and likewise the sum is divided by 2 to avoid double counting the (two) effects of shifting the same unit of electricity i.e. a reduction of demand at one time period *and* an increase of demand in another time period.

As changes to demand do not affect all generators equally but only those that operate on the margin, the model needs to account for the marginal impact of the demand response intervention. We use a simplified merit-order curve shown in Figure 1. This shows the different types of plant that operate on the margin depending on the level of system demand. The merit-order is largely based on the emissions intensity of the plant: nuclear is highest in merit and runs as baseload, while oil is last as it is most polluting. This reflects a general finding in power systems that the average emissions factor is lower than the marginal emissions factor (Hawkes, 2010; Siler-Evans et al., 2012). This merit-order is a simplifying assumption about merit-order for the purposes of illustrating concepts relevant to the evaluation of the carbon reduction potential of demand response. It reflects a situation where merit-order is aligned with carbon-order which, in practice, would be reliant on the carbon-order also reflecting the cost of generation. This would be unrealistic in the absence of a carbon tax or mechanism such as the EU Emissions Trading Scheme. Renewable energy is not included in this simple conceptual example as the focus is on how demand response affects generators operating on the margin, and renewable energy such as solar and wind do not operate on the margin, except in the case where they are being curtailed. The case-study in the following section will consider the case where the impact of the demand response is to reduce curtailment.

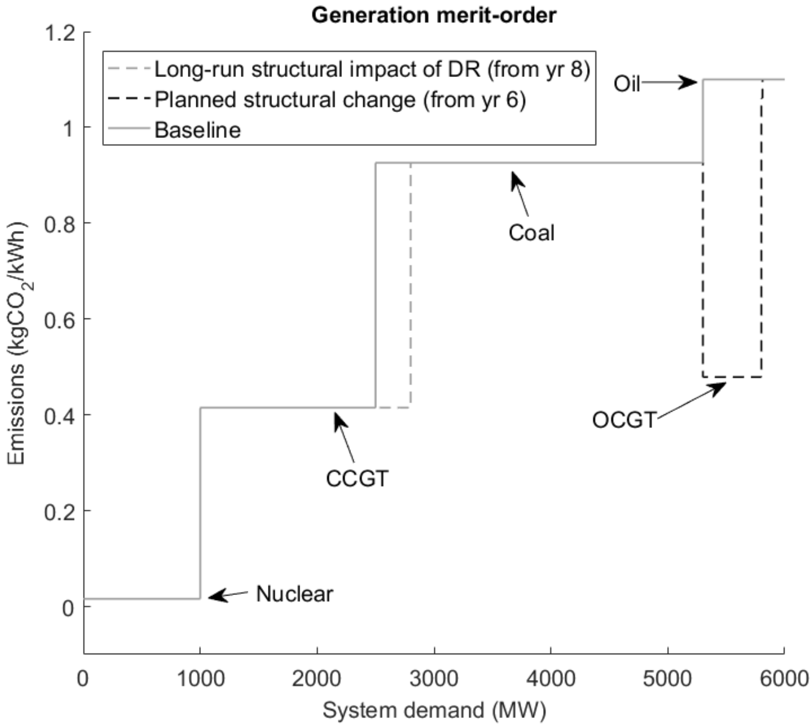


*Figure 1 – simplified merit-order curve used in the model. CCGT: closed cycle gas turbine, OCGT: open cycle gas turbine.*

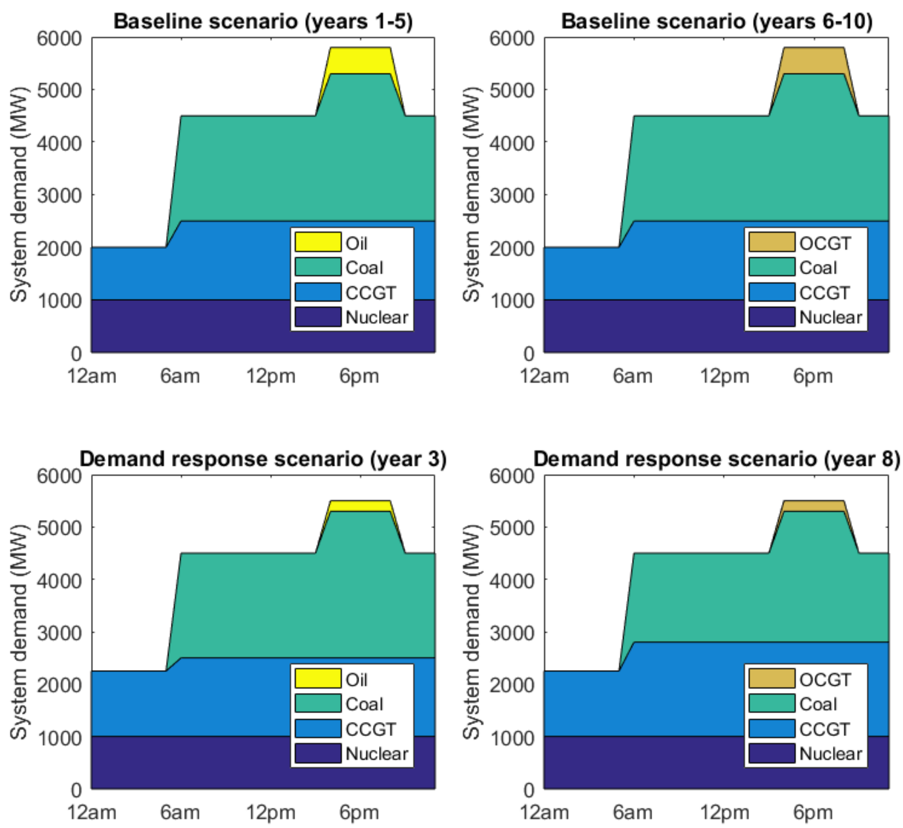


*Figure 2 – system demand profiles and dispatched generation for baseline and demand response scenarios. CCGT: closed cycle gas turbine, OCGT: open cycle gas turbine.*

The merit-order is used to dispatch plant to meet the system demand profile, as shown in Figure 2. A simplified 'blocky' demand profile is used, dividing the demand profile into peak, shoulder and off-peak periods. It is assumed that the demand profile is static for the whole year considered and that changes occur instantly from one year to the next. We account for planned structural changes to the power system. Over the ten-year time horizon considered here (years 1 to 10), the baseline scenario sees a change from year 6 onward, when some oil generation gets replaced with open-cycle gas turbines (OCGT), due to efforts to decarbonise the system e.g. as might be the result of a mechanism such as the EU Emissions Trading Scheme. This results in the marginal emissions factors at certain levels of peak demand being lower than they are during certain levels of 'shoulder' demand, as OCGTs are less polluting than coal (Figure 1). It is not unusual for this to occur in real power systems such as UK and USA (Hawkes, 2010; Siler-Evans et al., 2012).

The demand response scenario consists of a change in the demand profile compared to the baseline from year 3 onwards. The baseline peak demand is 5.8 GW which reduces to 5.5 GW from year 3 in the demand response scenario. All of this demand is shifted to the off-peak period which goes from 2 GW in the baseline to 2.25 GW from year 3 in the demand response scenario. The difference in change in power between the two periods is because the peak period is shorter in duration (5 hours), than the off-peak period (6 hours).

The results of the simple model's estimates of the demand response marginal emissions factor (DR-MEF) are shown in Figure 3 and Table 1. The demand response intervention is introduced in year 3 and we account for its short-run marginal impact. In years 3 through 5 the impact is to reduce generation and emissions from oil which operates on the margin during the peak, and increase generation and emissions from gas which operates on the margin during the off-peak. This 'gas for oil' substitution results in a DR-MEF of -0.65 kg$CO_2$ per kWh. To be clear, this means that each kWh of electricity load-shifted in time and that substitutes oil generation for CCGT results in a reduction in emissions of 0.65 kg$CO_2$. This estimate is based on $CO_2$ content by generation fuel type at point of demand found in (Hawkes, 2010). Over a year, each kWh shifted in this way reduces emissions by 236 kg$CO_2$, hence the units: kgCO2/kWh/yr.

In years 6 and 7 the impact is reduced as, due to planned structural changes to the system, the marginal emissions factor during the peak reduced (Figure 1). The effect of the demand response is to substitute OCGT for CCGT, resulting in a relatively small DR-MEF of -0.064 kg$CO_2$/kWh and annual impact (-23.4 kg$CO_2$/kWh/yr). This illustrates the case where the impact of demand response can be negligible in power systems that have relatively small time of day differences in marginal emissions factor. Indeed, when this is the case and if the load-shift is achieved at the expense of energy losses, as for example with batteries, then the impact may be negative (McKenna et al., 2016).

Finally, we account for the long-run impact of the demand response intervention. The long-run impact accounts for structural change that is precipitated by the intervention (Hawkes, 2014), and so which is in addition to structural change that was already ongoing e.g. the replacement of oil with OCGT. In the simple model, the result of the increase in baseload demand prompts the decision in year 8 to decommission 300 MW of coal plant to be replaced by a new 300 MW CCGT plant. The DR-MEF is higher than the straightforward 'coal for CCGT' swap for each unit of energy shifted because the demand response intervention can also claim the credit for the additional carbon savings associated with the new gas plant running at other time periods and displacing coal then too. The DR-MEF for years 8 through 10 is -1.9 kg$CO_2$/kWh and annual carbon savings are 695 kg$CO_2$/kWh/yr. This illustrates that long-run impacts of demand response can be positive and large compared to short-run impacts.

This section described a simple model to help illustrate some of the important concepts that should be considered when assessing demand response technologies. In particular, the assessment method should be of sufficient resolution to account for the temporal impact of the demand response intervention and account for a) how the power system responds to marginal changes (at high resolution) now, b) how that might evolve in the future given expected structural changes in response to external factors (e.g. decarbonisation efforts), and c) including long-run structural changes *precipitated by the demand response intervention itself*. To be clear, changes occur to generation anyway, and while not *attributable* to demand response, should be accounted for. This is not the full story, however, and accounting for structural changes that *are attributable* to the impact of the DR is also needed i.e. that would not have happened if DR had not taken place – this is the long run impact.

Real power systems are clearly much more complicated than the simplified example described here, and power systems simulations are therefore a necessary tool in assessments, as in (Darby et al., 2013). In particular, we have not considered i) renewable energy and how demand response interventions might affect periods of curtailment, ii) energy storage e.g. the operation of existing storage units such as pumped hydro plant, iii) realistic i.e. diversified impacts of distributed demand response interventions, and iv) constraints on generators such as ramp-rates, part-loading, network constraints and reinforcement, unplanned downtime, or ancillary services. Finally, we note that the above deals with the 'in-use' phase of a demand response technology, and a full life-cycle assessment also requires accounting for the impact of 'cradle-to-gate' and disposal phases.

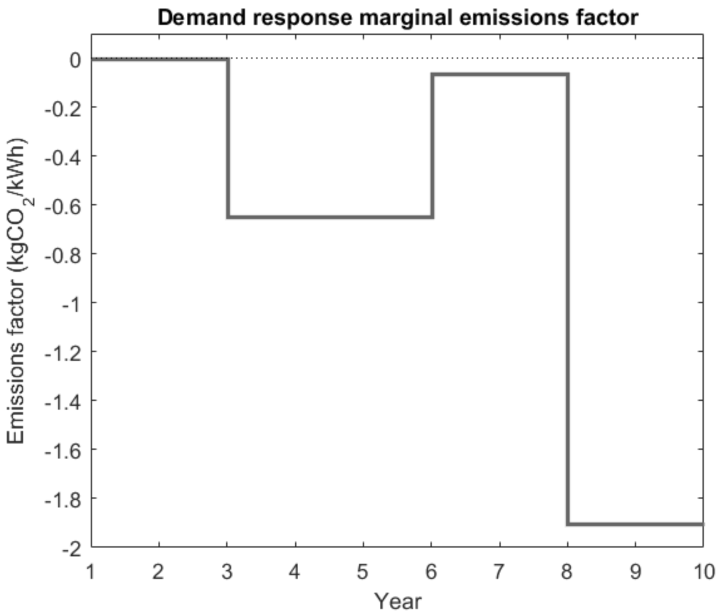


*Figure 3 – theoretical estimates of the demand response marginal emissions factor for the simple model.*

**Table 1 – results of the simple model.**

| Demand response scenario | Demand response marginal emissions factor (kgCO2/kWh) | Annual emissions impact of load-shift (kgCO2/kWh/yr) |
|---|---|---|
| 1. CCGT for oil | -0.65 | -236 |
| 2. CCGT for OCGT | -0.064 | -23.4 |
| 3. New CCGT plant built, replaces coal | -1.9 | -695 |

**Table 2 – results for the case-study of a domestic battery system (90% efficient) in the Irish power system**

| Demand response scenario | Demand response marginal emissions factor (kgCO2/kWh) | Annual emissions impact of load-shift (kgCO2/kWh/yr) |
|---|---|---|
| 1. Peak shaving and trough filling | 0.07 | 25.4 |
| 2. Avoiding wind curtailment | -0.49 | -179.3 |
| 3. New CCGT plant built, replaces average grid-mix | -2.6 | -955.2 |

## Case-study: domestic battery systems in the Irish power system

The previous section described a simple model to illustrate some of the important concepts that are useful to account for within a comprehensive assessment of the carbon impact of demand response technologies. A full assessment that accounts for all these points is out of the scope of this paper, however this section provides an indicative assessment for a real-world case-study: domestic battery systems in the Irish power system. The results are shown above in Table 2 alongside Table 1 for ease of comparison, and are briefly explained below along with the method.

Rows 1 and 2 provide estimates of the short-run DR-MEF based on various assumptions about battery operating strategies. These are equivalent to Table 1 rows 1 and 2 of the simple model results: they assume a substitution of marginal generation at one time period for marginal generation at another time period. The difference is that they are now based on empirical data, in particular previous work by estimating the environmental impact of storage systems in the Irish power system based on estimates of the short-run marginal emissions factor from several years of historic data of individual generator output (McKenna et al., 2016). The battery system is assumed to have a round-trip efficiency of 90%.

Row 1 provides the case for when the battery is charged during the peak and discharged during the off-peak or 'trough' period, a commonly assumed operating scenario for storage. The DR-MEF is positive, though small (0.07 $kgCO_2$/kWh), meaning the effect of this demand response action would be to *increase* emissions. This is because the Irish power system has similar marginal emissions factors during peak and off-peak times and the benefit of shifting from peak to off-peak is outweighed by losses in the battery system. It is similar to the simple model's case of substituting OCGT for CCGT: the impact is negligible, and indeed negative once round-trip losses are factored in.

Row 2 assumes that the operation of the storage changes the dispatch of generators and thus which generators are operating on the margin. The Irish power system has a particular issue to do with wind curtailment – where there is too much wind power and not enough demand and wind turbines need to be switched off (McKenna et al., 2015) – and row 2 shows the results for when the storage is charged to avoid wind curtailment and discharged to avoid the average marginal generation. In this scenario, wind power is the marginal generation because otherwise the wind power would be curtailed, and the effect of the battery charging is to reduce this. It is assumed that the storage can charge 100% with wind power. It is important to point out that otherwise wind power would not act on the margin, as it is not dispatched to meet changes in demand, and storage would not be 'charged with wind power', even if it operated in a 'wind following' pattern. The results show that the DR-MEF for this scenario is -0.49 $kgCO_2$/kWh and that operating storage in this way reduces emissions by 179.3 $kgCO_2$/kWh/yr.

Finally, row 3 estimates the long-run DR-MEF based on the assumption that the marginal impact of each kWh load-shifted from peak to off-peak resulted in one kW of additional new build CCGT assumed to operate at the same carbon intensity as the most carbon efficient gas generator on the Irish power system, the Tynagh Generator at 0.389 $kgCO_2$/kWh and operating at an equivalent capacity factor (0.69), which displaces electricity at the average marginal emissions factor (0.547 $kgCO_2$/kWh). The DR-MEF for this scenario is -2.6 $kgCO_2$/kWh with emissions savings of 955.2 $kgCO_2$/kWh/yr.

Given the simplicity of the method, these results should be viewed as indicative only. Nonetheless, they show that, based on historic data, the impact of demand response technologies in the Irish power system could be negligible, or even negative, unless the technology can be dispatched in such a way as to affect the generators that operate on the margin (e.g. avoiding wind curtailment, or replacing oil generation with CCGT) or unless it has a long-run structural impact e.g. enabling the decommissioning of old polluting plant to be replaced by new cleaner forms of generation. When these structural effects do occur, the impact can be positive and demand response technologies can achieve considerable reductions in emissions. This conclusions should be true for power systems with similar marginal emissions factor characteristics i.e. marginal emissions during off-peak that are similar or higher than they are during the peak, such as USA and UK (Hawkes, 2010; Siler-Evans et al., 2012).

## Discussion

### *Importance of enabling structural change*

The first point to note is that the results highlight the importance of enabling demand response technologies to achieve structural change such as affecting the dispatch of generation, but particularly the decommissioning of old polluting plant. Demand response technologies that do not achieve this kind of impact can have negligible, or even negative, impact on emissions, depending on the characteristics of the marginal emissions factors of the power system in question. A critical factor is where demand response specifically enables more renewable energy e.g. through reducing curtailment, or enabling installations that wouldn't have otherwise been built. It is important to enable beneficial structural change for example through cap-and-trade policies such as the EU Emissions Trading Scheme (Betz and Schmidt, 2016) It is arguable that a critical part of enabling this change is allowing demand response technologies to participate in power system markets for ancillary services, wholesale electricity, and particularly the capacity market as presumably this is where they can have the most impact on decommissioning peaking plant, which tends to be most polluting.

### *A role for demand aggregators*

The value of demand response technologies participating in power system markets points towards a clear role for demand aggregators. Smart appliances and the like are too small to participate in current markets, yet demand aggregators can serve as the necessary intermediary between these small distributed resources and the markets where their impact can have most benefit. The results show the potential difference in impact of demand response technologies that achieve structural impact compared to those that do not and, assuming this is correct, there is an argument that smart appliances should be enabled for demand aggregation as standard, as they would be adding considerable value in the form of lowering overall carbon emissions. This could involve the specification of minimum functionalities for smart appliances, depending on type, such that they can be effectively integrated into demand aggregator services and subsequent power system markets.

### *Regulation of appliances for demand response*

More broadly this leads to the subject of the regulation of smart appliances. The recent call for evidence from the UK Government and energy regulator Ofgem on smart flexible energy systems[2] demonstrates how governments have open questions regarding the extent to which smart appliances should be regulated. Following the Treasury Green Book's principle[3] that policies should be subjected to comprehensive but proportionate assessment, we would argue that, assuming the preliminary results shown here reflect a general finding, smart appliances should be subjected to a level of assessment at least as thorough as is the case for energy efficiency technologies. Currently, however, smart appliances are not assessed in a comparable manner and there are still many questions outstanding regarding which technologies best serve national interests. We would call for further work in this area, particularly regarding a standardised framework for assessing demand response interventions. This is a clear area in which a unified European framework would be of value, including standards for smart appliance labelling and minimum levels of functionality.

Finally, we note that here we have focussed on the sustainability aspect of smart appliances, but clearly they also have important impacts in terms of energy security and affordability, and we have not included any cost-benefit estimates which would be necessary to determine cost-effectiveness. It is important to assess smart appliances against all of these criteria to provide the best understanding of their role in achieving a sustainable, secure, and affordable energy future.

## Conclusions

The efficiency of low-carbon systems depends not only on policies that promote demand reduction, but also those that promote demand response. To inform policy decisions about smart appliances this paper addresses the question: how much could domestic demand response technologies reduce $CO_2$?

A review of selected literature on the emissions impact of smart technologies revealed that savings are often associated with improvements in energy efficiency, though gains in efficiency may be reduced or offset altogether by emissions incurred elsewhere e.g. through energy-use of additional sensors, or increased service expectations.

The potential impact of demand response is often not considered. Studies that do assess demand response indicate a range of possible impacts depending on the method and assumptions used. Studies based on short-run estimates indicate that demand response can have a negligible effect in certain power systems, and may even increase emissions e.g. due to efficiency losses in domestic battery systems.

By contrast, where long-run structural impacts are accounted for, then demand response can achieve considerable reductions in carbon emissions. Beneficial impacts include changing the dispatch of generation, reducing renewable generation curtailment, but particularly the decommissioning of peaking generation and replacement with (less polluting) base-load generation.

Given the value of achieving structural change, the findings highlight the beneficial role of the demand aggregator, who acts as the necessary intermediary between distributed small-scale resources of smart appliances and the electricity markets where their beneficial structural impacts can be most effectively enabled. More broadly, the paper indicates the need for greater assessment and regulation of smart appliances to maximise their potential benefits to society.

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[2] https://www.gov.uk/government/consultations/call-for-evidence-a-smart-flexible-energy-system

[3] https://www.gov.uk/government/publications/the-green-book-appraisal-and-evaluation-in-central-governent

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