Integrating wind power into the UK energy mix through dynamic demand-side response

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Abstract

In the majority of domestic demand-side response (DSR) programmes that have taken place, the principal driver for consumers to participate has been financial. However, on most programmes where consumers can benefit from cheaper electricity, they risk paying more if they use a lot of their electricity at peak times. As a consequence, consumers who are risk averse are likely to be less willing to participate in DSR programmes (Faruqui, 2010; Neuberg, 2013).

However, while some consumers might not be prepared to engage in price-based DSR, studies have shown that other motivations - such as helping to reduce the likelihood of power cuts or lowering environmental emissions - can motivate consumers to participate (Gyamfi & Krumdieck, 2011). At the same time, as the proportion of renewable energy in the system mix grows, the importance of residential DSR in helping to balance supply and demand is likely to increase (Alizadeh et al. 2016; Ward et al. 2014)

This paper describes a domestic DSR trial that took place in the England from May 2015 to September 2015. The trial examined how participants would respond to information only signals to vary their electricity use depending on prevailing generation from wind. During the trial, households were sent notifications requesting that they either increase electricity consumption ('turn up' events) or reduce electricity consumption ('turn down' events) depending on how much electricity was being generated from wind across the UK.

Electricity consumption was monitored throughout the trial and consumption during events was compared with a reference load which was established for each of the households. On average, trial households reduced their electricity consumption by 9.9% during 'turn down' events and increased their electricity consumption by 4.4% during 'turn up' events. The implications of these results for the use of non-financial DSR programmes to balance the supply of renewable energy with energy demand are discussed.

1. Introduction

Renewables are the second-largest generator of electricity in the world, after coal, and are set to overtake coal in the early 2030s (IEA 2015). In the UK, 64,654 gigawatt-hours of electricity were generated from renewables in 2014, with nearly half of this coming from offshore and onshore wind (Special feature – Renewable Energy in 2014). While rapid growth in renewable generation will be necessary if the UK is to decarbonise its electricity system and meet ambitious climate change targets, managing the variable nature of these resources requires increased system flexibility. As renewable generation displaces energy produced by conventional power plants, the need for ancillary services to balance supply and demand will increase. However, if these services are supplied by conventional generation running part-loaded, this will reduce the efficiency of system operation, undermine the potential to accommodate low carbon generation, increase emissions and lead to higher bills for consumers (Strbac, 2016).

In this regard, the National Infrastructure Commission has found that increasing capability for demand-side response (DSR) – along with greater use of interconnection and storage – could save consumers up to £8 billion a year by 2030, help the UK meet its 2050 carbon targets and secure the UK's energy supply (Smartpower, 2016). DSR can be defined as "customers responding to a signal to change the amount of energy they consume from the grid at a particular time" (Ofgem, 2013, 1). On most DSR programmes, this signal has taken the form of financial incentives for using electricity at certain times through two financial mechanisms: incentive payments and dynamic pricing (Kim and Shcherbakova, 2011; Chan et al, 2014; Song et al 2014). Incentive-based programmes use demand as a reserve to balance the power system and maintain reliable operation through direct load control or voluntary methods such as curtailable or interruptible programmes. Price-based programmes seek to improve the economic efficiency of power systems and include programmes such as time-of-use pricing, critical peak pricing and real-time pricing, which aim to flatten load curves by charging consumers lower prices in off-peak hours and higher prices in peak hours (ibid).

Residential demand-side response in the UK

In the UK, households are responsible for the largest share of electricity demand: 30% of total electricity consumption in 2014, a greater proportion than either the commercial sector (21%) or the industrial sector (26%)(Dukes, 2015). The residential sector also accounts for approximately half of all electricity consumed during the system peak between 5:00pm and 7:30pm (Hesmondhalgh et al, 2014). These features of residential demand – along with the fact that the electrification of heat and transport could double demand for peak electricity by 2030 (Pudjianto et al, 2013) – highlight the important role that residential DSR could play in changing patterns of electricity demand.

DSR tariffs have been available for domestic consumers in the UK for some time; around 4.5 million customers are already on multi-rate electricity tariffs, which provide discounted electricity during the night (Torriti et al, 2010). These tariffs – originally introduced in the 1960s – were designed to operate alongside night storage heaters to increase the use of continuous base load from nuclear generation during the night. In recent years, Ofgem has sponsored two trials examining how consumers respond to DSR tariffs: the Customer Led Network Revolution time-of-use trial and the Low Carbon London dynamic time-of-use trial. The former explored consumer response to a tariff which charged 99% above standard rates for electricity between 4:00pm and 8:00pm on weekday evenings and below standard rates at all other times (Wardle et al, 2013). On average, participating households reduced demand at peak times by 0.1 kW per hour (ibid). The latter trial explored how consumers would respond to a dynamic time-of-use tariff with variable rates which depended on prevailing generation from wind (Schofield et al, 2014). Households on the trial increased demand by an average of 0.1kW per hour during low price periods and decreased demand by an average of 0.1kW per hour during high price periods on weekdays that occurred during the morning and evening peaks (ibid).

2. Using non-financial considerations to motivate participation in DSR

While the commercial value of residential DSR programmes – and in particular, dynamic DSR – is likely to grow as the share of renewable energy in the system mix increase (Alizadeh et al, 2016; Strbac, 2016), it may be injudicious for suppliers to rely solely on financial incentives to encourage consumers to participate. Studies have shown that both loss-averse and risk-averse consumers are less willing to switch to DSR tariffs (Fell et al, 2015; Neuberg, 2013). The modest savings to be gained from financial DSR programmes may discourage other consumers from participating; analysis commissioned by DECC predicts that up to 2030, consumers on DSR tariffs will save less than £90 annually per household (Redpoint and Element Energy, 2012). As Kim and Shcherbakova (2011) argue, this limited potential for savings may mean that, “it may not be worth a customer’s effort to invest in understanding time-varying prices that demand response programs offer and to participate in them” (876).

These considerations suggest that financial incentives alone may be insufficient to motivate a broad range of domestic consumers to participate in DSR. Studies have shown that some consumers can be motivated to participate by considerations other than price (Gyamfi and Krumdiek, 2011; Strengers, 2010; Onzo, 2011). In a mail-back survey study conducted in Christchurch, New Zealand respondents were asked to indicate the importance of price, energy security and environmental protection as reasons for engaging in DSR; all three were found to be motivating, with security performing as strongly as price (Gyamfi and Krumdiek, 2011). In another study – in New South Wales from 2006-2008 – consumers were asked to reduce demand during dynamic DSR events. They responded, in the absence of financial incentives, by reducing demand by 13% during events in the summer and by 11% during events in the winter (Strengers, 2010). UK consumers have likewise reduced demand in response to information-only programmes. Between October 2010 and June 2011, Scottish and Southern Electricity issued 25,000 customers with in-home displays which provided a visual reminder between 4:00pm and 7:00pm that the electricity system was under increased load. Customers responded by reducing demand by an average of 5% at these times (Onzo, 2011).

The fact that some consumers are willing to engage in DSR in the absence of financial incentives has led to recommendations that further studies be commissioned to examine the use of non-financial signals to facilitate DSR (Hall et al, 2016; Song, 2014; Strengers 2010). Strengers, for example, suggests that since some consumers have non-rational motivations for responding to DSR programmes – such as a desire to contribute towards the 'common good' – "entrenched assumptions underpinning variable pricing programs need to be expanded and extended to consider other potential theories, methods and motivations for change" (ibid, 7320). Similarly, Hall et al (2016) suggest that further DSR research should be commissioned "to explore non-economic influences" (72).

While some studies have explored how consumers respond to electricity prices that vary according to wind generation (Schofield et al, 2014), no known studies have explored whether consumers would change their consumption patterns in response to information-only signals about the availability of wind power. This paper describes a trial conducted in Southern England from May to September 2015, which was designed to investigate two principal questions:

- Would participating households respond to information-only notifications about wind generation by changing demand patterns?
- If so, what level of response would they provide?

This paper describes the trial in detail. Section 3 explains how participants were recruited and provides socio-demographic details relating to the sample. Section 4 presents the experimental design and Section 5 summarises the results. Finally, Section 6 discusses some limitations of the research and conclusions.

3. Trial recruitment and participant socio-demographics

An invitation to participate in the trial was circulated through several channels, including the Centre on Innovation and Energy Demand website (Centre on Innovation and Energy Demand, 2015), the Your Energy Sussex Twitter account and the West Sussex County Council email bulletin. The call for participation explained that since electricity cannot be easily stored, DSR programmes of this nature could prevent electricity from being wasted and help to promote wind energy. In the event, 46 households from Southeast England agreed to participate.

Since participants self-selected for the trial, it is important to acknowledge the possible effect that sample selection bias may have had on the results of the study. Ek and Söderholm (2010) have shown that participants who choose to participate in energy-saving experiments often have high levels of environmental awareness and are inherently motivated. However, rather than representing a drawback in the methodological approach, the fact that the sample was likely to consist of consumers with greater environmental awareness was considered advantageous: the study aimed to investigate how environmentally motivated consumers would respond to requests to change household consumption patterns.

In order to obtain socio-demographic information about the households, participants were asked to complete an online questionnaire. Table 1 provides details.

Table 1: Socio-demographic information

Household location	East Sussex	20
	West Sussex	12
	London	8
	Other[1]	6
Household ownership	Owner	35
	Renter	11
Gender - lead participant	Male Female	25 21
Household members	1	4
	2	15
	3	7
	4	16
	5+	4
Household income	£100 - £199	1
	£200 - £299	1
	£300 - £399	2
	£400 - £499	3
	£500 - £599	1
	£600 - £699	0
	£700 - £799	3
	£800 - £899	4
	£900 - £999	7
	£1000+	15
	Don't know/prefer not to say	9

Compared to members of the UK as a whole, participants came from households with greater than average combined household incomes and were also more likely to own their own homes (Office for National Statistics, 2012). On average, participating households were also somewhat larger, with a larger share of four-person and five-person+ households than average for the UK (ibid).

[1] West Midlands, Cornwall, South East, Norfolk, Portsmouth, Cambridge

4. Experimental design

Data collection

Three devices were used to set up the experiment:

- a device for measuring household electricity consumption, which was attached to each household's electricity meter;
- an in-home display; and
- an 'internet bridge'.

The in-home display allowed participants to choose to display real-time information about their energy consumption in either kilowatt-hours (kWh), expenditure or carbon dioxide emissions per hour. By default it showed consumption in pence per hour as seen in Figure 1.

Figure 1: Geo Solo II in-home display

The internet bridge was connected to each household's broadband router, enabling household members – as well as the project analyst – to access detailed electricity consumption information via the 'energynote' platform (Energynote, 2014). This information included historical electricity consumption data presented either daily, weekly, monthly or seasonally. The data was recorded at 15-minute intervals and downloaded for analysis from the energynote accounts.

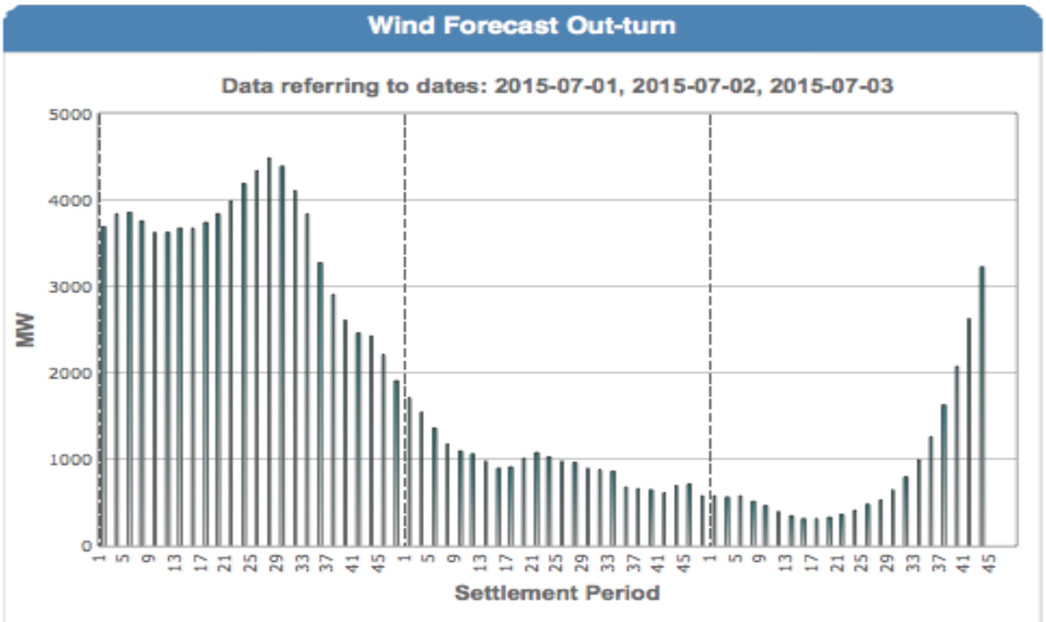
Events

Twenty-four 'turn-up' events, where participants were asked to increase their electricity consumption, and 16 'turn-down' events, where participants were asked to reduce consumption, were held between 23 June 2015 and 5 September 2015. Five events took place in June, 19 in July, 14 in August and two in September. Each event lasted for between two and 18 hours. Households registered one or more mobile phones on which to receive event notifications by text and could also opt to receive notifications by email. Two notifications of each event were sent: the first a day in advance and the second an hour beforehand. The first gave participants the opportunity to plan how they might respond during the event, while the second reminded them that the event was about to start.

Timing
The timing of events was based on information from National Grid's wind forecasting tool, which is published on the Balancing Mechanism Reporting System (BMRS) website (BM Reports, 2014). The tool forecasts total electricity generation for the following 72 hours from windfarms visible to National Grid (combined capacity of 8972 MW). This data was analysed daily throughout the trial in order to determine the timing and duration of events. Turn-down events were scheduled for periods when predicted output from all wind farms combined was under 850 MW, which represents under 10% of maximum installed wind capacity. Turn-up events were scheduled when predicted output from all wind farms combined was over 3000 MW, representing more than 33% of total installed wind capacity.

Figure 2 shows an example of this forecast data for the period between midnight on 1 July 2015 (the first '1' on the X axis) and 10:00pm on 3 July 2015 (the last '45' on the X axis). Minimum generation was predicted to take place between 7:00am and 11:00am on 3 July (15-23 on the X axis). Since generation was forecast to be under 850 megawatts over this period, a turn-down event was scheduled (Event 7).

Figure 2: Forecast of total electricity generation from windfarms monitored by National Grid



The timing of events is shown in Tables 2 and 3. The green events in Table 2 were turn-up events (n=24) and the red events in Table 3 were turn-down events (n=16).

Table 2: Turn-up events

Event number

	3	4	6	8	10	11	13	14	15	17	19	21	22	23	25	27	29	32	33	34	35	36	39	40
12am																								
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Table 3: Turn-down events

Event number

	1	2	5	7	9	12	16	18	20	24	26	28	30	31	37	38
12am																
1am																
2am																
3am																
4am																
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Estimating demand response

The study used a within-subjects design, since all participating households were subject to all treatments. Estimations of response were calculated by comparing average electricity consumption values calculated for the households over a six-week baseline monitoring phase – which took place from 10 May to 22 June – with consumption values which were recorded during events.

h = household ($h=1,..N_h$)
k = event ($k=1,..N_k$)
i = baseline monitor period ($i=1,..N_{hk}$)
N_{hk} = number of baseline monitor periods for event k in household h
RC_{hki} = energy consumption in baseline monitor period i for event k in household h (kWh)
RC_{hk} = baseline energy consumption for event k in household h (kWh)

Reference consumption (RC_{hk}) values were calculated for each household (h) for each event period (k) – where the latter is defined as the the day of the week and the period during the day of the corresponding event. This involved measuring the electricity consumption in each household during each of the periods within the monitoring stage that corresponded with the events ($i=1,...N_{hk}$), and taking the mean:

$$RC_{hk} = \left(\frac{1}{N_{hk}}\right)\left(\sum_{i=1,N_{hk}} RC_{hki}\right)$$

The resulting values (RC_{hk}) provide estimates of the counterfactual: in other words, what the electricity consumption in the households would have been during those event periods had they not been exposed to the treatment.

Since household routines which affect electricity consumption are more likely to recur at similar times (Cetin et al, 2014; Powells, 2014), RC_{hk} values were calculated from consumption data collected over the same hours and on the same days of the week as the events themselves. This approach increased the likelihood that the values would reflect the typical electricity consumption of the households for these periods. To further reduce the potential for bias, reference consumption values were only calculated for event periods where a minimum of three data points were available (ie,$N_{hk} \geq 3$). This helped to ensure that RC_{hk} values would be a credible representation of typical demand: using participants' own consumption data as a reference load requires the availability of multiple data points with similar conditions to those observed during events (Cappers, 2013).

The second stage of the analysis involved calculating the difference between the consumption of each household during the event period (EC_{hk}) and the corresponding reference consumption (RC_{hk}). This was expressed in absolute terms (Δ_{hk}) and as a percentage (P_{hk}) of the reference consumption:

$$\Delta_{hk} = EC_{hk} - RC_{hk}$$

$$P_{hk} = \frac{(EC_{hk} - RC_{hk})}{RC_{hk}} * 100$$

Missing data

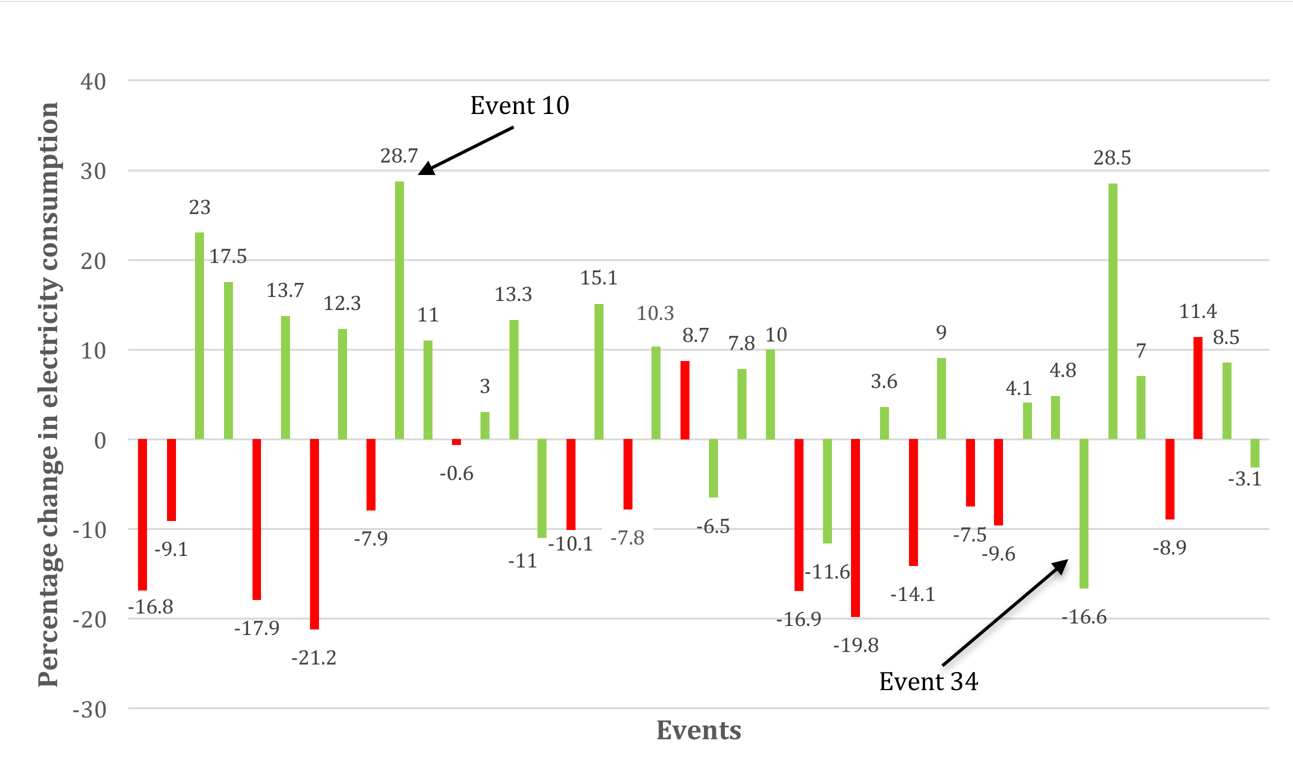
Occasionally, it was not possible to produce RC_{hk} or EC_{hk} values for particular households for particular event periods (k), due to missing data. In most cases, this occurred because in-home displays had been accidentally unplugged. However, in the case of one household, problems with the electricity supply led to missing data. In all cases where data was missing for a household for an event the household's data for that event was excluded from the analysis to prevent bias.

5. Results

Event response

Figure 3 shows the percentage change in electricity consumption for all households combined for each event relative to the reference consumption for all households combined. Turn-down events are shown in red and turn-up events are shown in green.

Figure 3: Combined household response during events



Of the 40 events held, 16 were turn-down events and 24 were turn-up events. The combined consumption of the households during turn-down events was lower than corresponding combined reference consumption values for 14 of the 16 events. The combined consumption of the households during turn-up events was higher than corresponding combined reference consumption values for 19 of the 24 events. Further details regarding the events – including comparisons between reference and actual event consumption as well as significance tests – are set out in Tables 4 and 5.

The greatest response was recorded during Event 10 (from 1:00pm to 4:00pm on 6 July), when households used 28.7% more electricity than during the corresponding reference period (13.42 kWh more electricity). At the other end of the spectrum, the lowest response was recorded during Event 34 (from 10:00am to 9:00pm on 23 August), when households used 16.6% less electricity (44.57 kWh), even though they had been asked to try to increase consumption. The anomalous response to this and several other turn-up events (Events 15, 21 and 25) was explored in the post-trial interviews and was found to have resulted from household members being away from home during these events, and as such consuming minimal electricity.

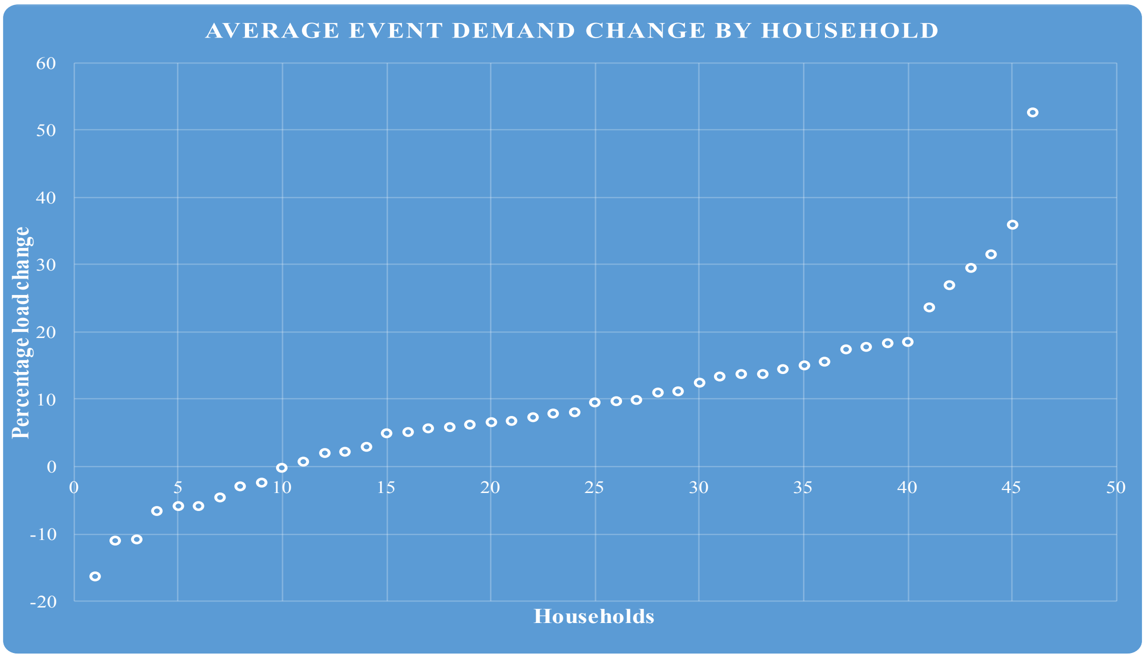
Participant response

In line with recommended practice (Cappers, 2013), and to facilitate comparison of the response seen in this study with other DSR studies, two measurements of response are reported:

- Average kWh change per event hour – the mean household response per event hour to turn-up events was 18.3W and the mean household response to turn-down events was 44W. The mean household response per event hour across both event types was 30W.
- Average percentage change in energy use per event hour – this was an average decrease in electricity use of 9.9% per hour for turn-down events and an average increase in electricity use of 4.4% for turn-up events. The mean household percentage change in consumption per event hour taking into account both turn-up and turn-down events was 6.8%.

As was also seen in the Customer Led Network Revolution and Low Carbon London DSR trials (Schofield, 2014; Bulkeley, 2014), there was considerable variability in the response provided by households, with the average percentage change in household consumption to all events ranging from -16% for the least responsive household to +52% for the most responsive household. Negative percentages indicate that a household tended to consume more electricity than its reference consumption during turn-down events and/or less electricity than its reference consumption during turn-up events.

Figure 3: Average percentage change in electricity demand by household



The response from households was also ranked in terms of load shifted (in kWh/event hour). This revealed considerable variation in response: the response from the top 25% of households was three times greater (approximately 100W) than the average response.

The 30W average response per hour provided by households during events equates to approximately 3.5% of the average winter peak household load (Carmichael et al, 2014). This is considerably less than the mean response of 100W provided by households on the Low Carbon London trial, which incentivised response using dynamic pricing (ibid). However, although the absence of financial incentives may have played a role in this difference, other contextual differences between the trials are noteworthy. First, the frequency of events was greater – just under four per week (3.73) – than the maximum of three events which were permitted per week on the Low Carbon London trial (ibid); a smaller response might be expected when participants are asked to respond more frequently. As one of the participants subsequently interviewed explained: “There was a phase when you were sending a lot of alerts very frequently one after another, and after that when you slowed it down again I was fatigued, – I mean, still fatigued even though you had slowed it down again.” (Participant 23)

Another factor that may help to explain the greater response on the Low Carbon London trial is that participants also received event notifications on their in-home displays. Studies have shown that response on dynamic DSR programmes is usually greater when participants are notified of events via a combination of text, phone and in-home displays (VaasaETT, 2011). Several participants who were interviewed for the current study also suggested that notifications on their in-home displays would have facilitated response.

Statistical analysis on event response

Statistical tests were carried out on the data to examine whether the changes in demand during the events were statistically significant. The combined event consumption of all households (CEC) was greater than the combined reference consumption of all households (CRC) for 19 of the 24 turn-up events (see Table 5). Similarly, the combined event consumption of all households (CEC) was lower than the combined reference consumption of all households (CRC) for 14 of the 16 turn-down events. Paired samples t-tests were carried out on the reference consumption and event consumption values of all households for each event to determine whether the changes in electricity demand during the events were statistically significant. For events which asked participating households to reduce (increase) consumption, the hypothesis tested was that households would reduce (increase) consumption during the events relative to their corresponding reference consumption value.

The tests revealed statistical significance (P=<0.05) for four of the turn-up events (representing 17% of these events) and for six of the turn-down events (representing 38% of these events). A further four turn-down events (representing 25% of these events) were significant at the 10% significance value (these all had P values <0.065). The mean difference between event consumption and reference consumption values is reported for each event in Tables 4 and 5, along with the 95% confidence intervals and significance values.

Since not all of the events were statistically significant, an additional paired samples t-test was performed – this time on all 40 events. The null hypothesis for the test was that the combined event consumption (CEC) of the households during the events was not significantly different from the combined reference consumption (CRC) during events. Before proceeding with the test, the data was transformed to enable both turn-up and turn-down events to be tested. The transformation meant that when the households reduced demand during turn-down events, this would be treated as a positive response.

The mean combined reference consumption for the events was 102.75 kWh and the mean combined event consumption was 110.13 kWh. The difference between the sample mean combined reference value and the mean value for events was 7.38 kWh, with a 95% confidence interval from 2.33 kWh to 12.43 kWh; the *t* test statistic was 2.957, with 39 degrees of freedom and an associated *p*-value of 0.005. As such, the null hypothesis was strongly rejected: *the combined electricity consumption of the trial households during events was statistically different from their consumption during the reference periods.*

Table 4: Events which asked participants to reduce electricity consumption

Event	Date	Day	Event time	Hours	CRC (kwh)	CEC (kwh)	Difference (kwh)	Percentage consumption change (%)	Mean difference per household	95% confidence interval of the difference		Sig. (1-tailed)
										Lower	Upper	
1	23.6.15	Tue	5pm-10pm	5	118.01	98.19	-19.82	-16.79	-.48349	-.84602	-.12095	.005
2	25.6.15	Thu	7am-10am	3	57.54	52.32	-5.22	-9.07	-.12147	-.25060	.00766	.032
5	29.6.15	Mon	6am-9am	3	50.46	41.44	-9.02	-17.87	-.21469	-.36155	-.06783	.002
7	3.7.15	Fri	7am-11am	4	75.65	59.63	-16.02	-21.18	-.37249	-.57773	-.16724	.000
9	5.7.15	Sun	6am–9am	3	42.98	39.57	-3.41	-7.93	-.07942	-.17487	.01604	.050
12	9.7.15	Thu	4pm-10pm	6	121.03	120.41	-0.51	-0.62	-.01483	-.36550	.33583	.466
16	19.7.15	Sun	9pm-12am	3	54.44	48.96	-5.48	-10.07	-.13714	-.30224	.02797	.050
18	22.7.15	Wed	8am-10am	2	34.82	32.09	-2.73	-7.84	-.06827	-.27928	.14273	.258
20*	24.7.15	Fri	7am-2pm	7	122.60	133.22	+10.62	+8.66	.26540	-.24007	.77087	.853
24	31.7.15	Fri	1am-8am	7	76.79	63.84	-12.95	-16.86	-.32379	-.52190	-.12568	.001
26	7.8.15	Fri	6am-12am	18	324.69	260.34	-64.35	-19.82	-1.60887	-2.47494	-.74281	.000
28	11.8.15	Tue	4pm-10pm	6	146.04	125.5	-20.54	-14.06	-.46693	-1.06357	.12970	.061
30	15.8.15	Sat	4pm-12am	8	165.50	153.07	-12.43	-7.51	-.28898	-.80344	.22549	.131
31	17.8.15	Mon	6am-12am	18	341.64	308.67	-32.97	-9.65	-.76681	-1.69698	.16335	.052
37	28.8.15	Fri	6am-10am	4	72.40	65.97	-6.43	-8.88	-.14944	-.40335	.10447	.121
38*	29.8.15	Sat	7pm-12am	5	102.08	113.76	+11.68	+11.44	.26539	-.13607	.66685	.905

*During these events the combined event consumption of all households (CEC) was larger than the combined event consumption of all households (CRC) despite the event calling for reduced consumption.

Table 5: Events which asked participants to increase electricity consumption

Event	Date	Day	Event time	Hours	CRC (kwh)	CEC (kwh)	Difference (kwh)	Percentage consumption change (%)	Mean difference per household	95% confidence interval of the difference		Sig. (1-tailed)
										Lower	Upper	
3	26.6.15	Fri	8pm-10pm	2	47.58	58.53	+10.95	+23.01	.26074	-.02855	.55003	.038
4	28.6.15	Sun	7am-12pm	5	89.09	104.63	+15.54	+17.46	.37907	-.22859	.98674	.107
6	1.7.15	Wed	10am-3pm	5	74.97	85.28	+10.31	+13.75	.23986	-.10781	.58753	.085
8	4.7.15	Sat	1am-7am	6	59.67	67.03	+7.36	+12.33	.17531	-.08912	.43974	.094
10	6.7.17	Mon	1pm-4pm	3	46.83	60.25	+13.42	+28.66	.31212	.00034	.62389	.025
11	7.7.15	Tue	8pm-12am	4	80.68	89.52	+8.84	+10.96	.21057	-.08876	.50990	.081
13	11.7.15	Sat	6pm-11pm	5	105.49	108.69	+3.2	+3.03	.07610	-.39211	.54430	.372
14	16.7.15	Thu	8pm-12am	4	74.87	84.80	+9.93	+13.26	.24216	-.02167	.50599	.035
15*	17.7.15	Fri	9am-4pm	7	111.92	99.55	-12.37	-11.05	-.30938	-.65187	.03312	.963
17	21.7.15	Tue	10am-3pm	5	81.93	94.30	+12.37	+15.10	.30166	-.29134	.89466	.155
19	23.7.15	Thu	9am-4pm	7	104.43	115.18	+10.75	+10.29	.26867	-.21510	.75245	.134
21*	25.7.15	Sat	7am-2pm	7	125.37	117.18	-8.19	-6.53	-.21563	-.66137	.23010	.834
22	27.7.15	Mon	9am-3pm	6	94.27	101.66	+7.39	+7.84	.19442	-.26776	.65660	.200
23	29.7.15	Wed	10am-3pm	5	71.58	78.72	+7.14	+9.97	.18310	-.22418	.59039	.184
25*	4.8.15	Tue	3pm-8pm	5	105.58	93.28	-12.3	-11.65	-.30757	-.73928	.12413	.921
27	8.8.15	Sat	4pm-12am	8	156.16	161.72	+5.56	+3.56	.13895	-.76893	1.0468	.379
29	13.8.15	Thu	8pm-12am	4	78.83	85.9	+7.07	+8.97	.16075	-.14393	.46543	.146
32	19.8.15	Wed	7pm-12am	5	102.76	106.97	+4.21	+4.10	.10261	-.45454	.65976	.356
33	20.8.15	Thu	8pm-4am	8	113.85	119.33	+5.48	+4.81	.13036	-.23430	.49501	.237
34*	23.8.15	Sun	10am-9pm	11	268.65	224.08	-44.57	-16.59	-1.01289	-1.91319	-.11258	.986
35	26.8.15	Wed	9am-4pm	7	107.82	138.56	+30.74	+28.50	.71485	-.001889	1.43159	.025
36	27.8.15	Thu	9am-4pm	7	108.32	115.93	+7.61	+7.02	.17707	- .20598	.56012	.178
39	3.9.15	Thu	10am-4pm	6	93.09	100.97	+7.88	+8.46	.17501	-.35907	.70909	.256
40*	5.9.15	Sat	9am-1pm	4	89.445	86.68	-2.76	-3.08	-.06144	-.40240	.27951	.641

* During these events the combined event consumption of all households (CEC) was smaller than the combined event consumption of all households (CRC) despite the event calling for increased consumption

6. Discussion

A key finding of this study was that the majority of households responded to the dynamic DSR events by making changes to consumption patterns. Overall, the households consumed 9.9% less electricity on average during turn-down events and 4.4% more electricity on average during turn-up events. This response is significant in light of the fact that participants received no financial incentives for their response. It suggests that initiatives such as that explored in this trial could supplement traditional financial DSR programmes: these programmes could represent an additional DSR resource by enabling a larger number of consumers to participate in DSR than would be the case if only financial programmes were offered.

However, although suppliers might have an interest in developing non-financial DSR programmes to benefit from reduced wholesale costs (UK Power Networks, 2014), it is moot whether consumers would be prepared to participate in such schemes if they were aware that suppliers would benefit financially from their response. This issue was raised in one of the post-trial interviews, with the participant suggesting that he would not be prepared to take part in non-financial DSR programmes if they were offered by suppliers for precisely this reason. This echoes the findings of Buchanan et al (2016): residential consumers in that study suggested that since their engagement yielded financial benefits for the grid and suppliers, they should share in those benefits.

As such, it is important to consider which organisations would be best placed to instigate non-financial DSR programmes. It is perhaps new entrants and non-conventional operators in the energy system – operating under what Ofgem refers to as 'non-traditional business models' – that might be the most likely candidates (Ofgem, 2015). Examples would include the non-profit supply companies established by Bristol and Nottingham councils: Bristol Energy and Robin Hood Energy, respectively. Such organisations may be a better fit for non-financial DSR programmes than conventional suppliers, since consumers are more likely to engage with non-financial DSR programmes if these are offered by non-profit players. Similarly, distribution network operators might have an interest in developing non-financial DSR programmes to defer the need for reinforcement work on the distribution network or to address capacity shortfalls in particular network areas (UK Power Networks, 2014). One distribution network operator, Electricity North West, has already run such a programme: the 'Power Saver Challenge'. This involved a competition between households in different districts in Stockport to use less electricity between 4:00pm and 8:00pm in Winter 2015 (Power Saver Challenge, 2015).

Finally, non-financial DSR programmes could also provide a resource for managing electricity flows in network areas where there are high levels of local generation. As highlighted by Work Steam 6 (2014), community schemes are one way to encourage the use of electricity proximal to its generation, thereby avoiding thermal or voltage issues. The report suggests that instead of financially rewarding individual customers for responding, benefits could “be directed towards sources of value to the whole community affected by the network constraint and prepared to provide an appropriate response” (ibid, 18)

Limitations

There are several important limitations to this study. The first concerns the small sample size (n=46); it is questionable whether scaling up such a programme would lead to corresponding levels of response (Pollitt & Shaorshadze, 2011). That scaling up non-financial DSR programmes might lead to reduced per capita response is supported by a meta-analysis of DSR programmes by VaasaETT (2011), which found that response to DSR tariffs was normally lower on programmes with larger numbers of participants.

The second relates to the fact that the trial ran for four months only. This raises two questions. First, although participants responded to the events by making consumption changes, it is not clear whether this response would have been sustained over a longer timeframe; some experts suggest that four months is not long enough to reach firm conclusions in this regard (Van Dam et al, 2010). Had the trial lasted longer, ‘response fatigue’ (Kim and Shcherbakova, 2013) might have led some participants to respond less or cease responding altogether. On the other hand, some argue that the response of participants on DSR programmes can actually increase over time as new ways of responding are embedded in everyday practices (Sexton et al, 1987; Filippini, 2011; Thorsnes, 2012; Breukers & Mourik, 2013).

Second, patterns of electricity demand vary at different times of the year, so the study does not reveal whether response at other times of year – for example, in winter – would be higher or lower (Hu et al, 2015). In this regard, however, evidence from other DSR studies suggests that the response could well have been greater had the study taken place in winter. Both VaasaETT (2011) and the Low Carbon London Dynamic Time of Use Trial (Schofield et al, 2014) found that response to non-automated dynamic DSR was greater during winter than at other times of the year. The post-trial interviews also support this conclusion: several participants commented that they would have been able to respond more in winter owing to their greater use of electric heating and electric cooking appliances at this time of year.

Finally, response may have been biased because participants were aware that they were taking part in an experiment – sometimes referred to as the ‘Hawthorne effect’ (Benson, 2000). This effect is often most noticeable in shorter experiments, as participants have less time to grow accustomed to the intervention, and must be factored in to avoid overestimating the impact of interventions (Darby, 2011).

The considerations discussed above suggest it would be imprudent to assume that the response seen on this trial would be replicated by future programmes taking place in different contexts. Nevertheless, the fact that many of the participating households responded to the events by altering demand patterns is encouraging and suggests that further studies to explore consumer response to non-financial DSR programmes would be valuable. These should ideally involve larger samples and be carried out over longer timeframes; this would make it possible to determine whether the response seen in this study could be replicated across a larger cohort of households and whether response would be sustained over time.

7. References

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8. Keywords

Demand-side response, renewable energy, behaviour change, load shifting.