Smart Scheduling of Household Appliances to Decarbonise Domestic Energy Consumption

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***Abstract*—Demand side response (DSR) and the inter-connectivity of smart technologies will be essential to transform and revolutionize the way consumers engage with the energy industry. The carbon intensity of electricity varies throughout the day as a result of emissions released during generation. These fluctuations in carbon intensity are predicted to increase due to increased penetration of variable generation sources. This paper proposes a novel insight into how reductions in domestic emissions can be achieved, through the scheduling of certain wet appliances to optimally manage low carbon electricity. An appliance detecting and scheduling algorithm is presented and results are generated using real demand data, electricity generation and carbon intensity values. Reductions were achieved from the variations in grid carbon intensity and the availability of solar generation from a household photovoltaic (PV) supply.**

I. Introduction

DUE to global concerns of climate change, there has been an ever-increasing focus on the decarbonisation of the energy industry [1]. Decarbonising domestic energy consumption is an important step towards achieving low carbon future.

Aghaei *et al.* explored the potential for DSR to fundamentally alter grid fuel mix by enabling intermittent renewable energy sources (RESs) such as wind and solar [2], albeit this is only at a conceptual level. Cooper *et al.* analysed the impact of emissions of heat pumps and micro-cogenerators participating in DSR [3]. This was a small scale, technology-specific study but results showed that DSR programmes with heat-pumps could cause significant reductions in CO_2 emissions. Lau *et al.* considered the carbon savings in a number of DSR initiatives, comparing the business-as-usual case with various smart DSR intervention programmes [4]. Smith *et al.* explored how DSR, capacity planning and carbon emissions will interact in the future. It was concluded that, contrary to expectations, DSR carried out to reduce peak load did not increase carbon emissions. However, this paper does not explore how carbon emissions can be actively minimised through DSR.

The current literature on DSR focuses on economic incentives, for example the application of Time-of-Use (ToU) tariffs to encourage consumers to reduce their consumption during periods of high demand. Ozturk *et al.* used a ToU tariff within a self organising home energy network to reduce prices for the customer [5]. DSR can help to reduce peak demand through the coordinated control of electric vehicles (EVs), and PVs [6], [7]. Amongst the literature, there are papers which model specific appliances, for example Good *et al.* considered DSR based on thermal energy storage in the form of hot water storage [8]. One of the methods to achieve reduced expenditure on electricity bills without compromising electricity needs is via a home energy management system (HEMS) [9]. HEMSs allow consumers to participate in the optimal management of renewable energy, storage and EVs whilst meeting any constraints set by the distribution network operators. A HEMS allows consumers to monitor, control and manage household appliances. In most of the literature a HEMS was employed to carry out DSR by means of appliance monitoring and communication infrastructure. Gosselin *et al.* studied the optimal management of storage and EVs as part of an HEMS when subject to financial constraints [10]. The paper looked into how bi-directional charging of EVs and energy storage can result in a household becoming better adapted to respond to generation. Joo *et al.* proposed a HEMS with multiple smart homes. The control of appliances are managed by the local HEMS, whilst energy storage and power trading between households is carried out via the global HEMS [11].

In summary, the literature presents many examples of how DSR can result in financial savings for the consumer, reduce peak demand and help stabilise the grid. However, the variability of grid carbon intensity on a daily basis is rarely considered as an incentive for DSR. With increasing shares of variable generation technologies, such as wind and solar, it is vital to manage the availability of low carbon electricity. Different from existing research, this paper conducts novel research on the variability of electricity carbon intensity and how appliance scheduling can minimise domestic carbon emissions. It investigates the carbon footprint of two wet appliances (washing machine and dishwasher) when scheduling their start time to minimise carbon intensity. Results were generated using a real time carbon intensity that integrates the carbon intensity of the grid with renewable energy such as PV. This paper creates a model to detect the appliances in the real demand data and reschedules these appliances to minimise carbon footprint. A simulation was then built to detect and reschedule appliances throughout the year to determine the impacts of rescheduling appliances and installing PV.

The remainder of this paper is organised as follows: Section II presents system and algorithm. Simulations and discussions are presented in Section III, and Section IV draws conclusions.

II. System and Algorithm

A. Carbon Emission

Carbon intensity values for grid electricity consumption are generated using 2018 grid generation data [12] and generation carbon intensity factors as shown in Table I [13].

TABLE I
CARBON INTENSITY BY GENERATION TYPE.

Generation Type	2018 Demand	CO_2e (g/kWh)
Coal	5.8%	910
Nuclear	23.0%	0
CCGT	43.7%	360
Wind	14.9%	0
Pumped Storage	0.9%	0
Hydro	1.2%	0
Biomass	6.1%	300
Oil	0%	610
Solar	4.1%	0
OCGT	0%	480
French Interconnector	-	90
Dutch Interconnector	-	550
Irish Interconnector	-	450

Firstly, the model generates a carbon intensity of grid electricity at time t, C_g^t, using (1). It sums the individual contributions of emissions from different generation types to produce a real-time carbon intensity value depending on the energy mix. The grid carbon intensity is given by:

$$C_g^t = \sum_{k=1}^{K} \left[\frac{D_k^t}{D_{total}^t} C_k^t \right] \tag{1}$$

where, at time t, k represents the generation type, D_k^t represents the national electricity generation from k, D_{total}^t is the total national electricity demand and C_k^t is the carbon intensity factor for k.

The carbon intensity of household electricity consumption, C_h^t, includes electricity contributions from the grid and from the household PV supply. It is calculated using (2):

$$C_h^t = \frac{P_g^t C_g^t + P_s^t C_s^t}{P_g^t + P_s^t} \tag{2}$$

where P_g^t and P_s^t represent the electricity taken from the grid and PV system respectively at time, t. C_g^t is the carbon intensity of the grid, calculated using (1) and C_s^t is the carbon intensity of electricity from the household PV supply.

The amount of electricity taken from the grid, P_g^t is calculated using (3):

$$P_g^t = P_d^t - P_s^t \tag{3}$$

where, at time t, P_d^t the electricity demand of the household and P_s^t is the electricity generated from the household PV source. The carbon intensity for the household PV source, C_s^t is taken to be zero. There is a carbon intensity associated with the embedded carbon of PV cells during manufacture. However, this is disregarded for the scope of this model as the carbon intensity factors in Table I do not include the embedded carbon of plant construction.

It can be seen in (2) that when there is no PV generation ($P_s^t = 0$) the household carbon intensity equals grid carbon intensity ($C_h^t = C_g^t$). When the PV generation exceeds the household demand, $P_s^t > P_d^t$, then $P_g^t < 0$ and this represents the case where there is a surplus of PV generation. In this case, the renewable energy could be sold back to the grid. This will be important in future scenarios when PV exports can be curtailed to manage energy balancing and network issues.

However, this model does not include the option to sell electricity back to the grid. The electricity taken from the grid is taken to be zero when there is a surplus of electricity generated from the PV supply, $P_s^t > P_d^t$. Equation (4) is applied to ensure the calculated household carbon intensity is always a positive integer of zero:

$$P_g^t = \begin{cases} P_d^t - P_s^t & \text{if } P_d^t > P_s^t \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The carbon emission calculator provides a household carbon intensity (gCO_2e/kWh) which represents the carbon emission per kWh of electricity consumption in the household. Fig. 1 shows an example of the calculated carbon intensity on a typical summers day with Fig. 1(a) showing the carbon intensity of the national grid electricity and a typical daily household PV generation. The model combines these two data sets with the demand data to produce a carbon intensity of the household, shown in Fig. 1(b).

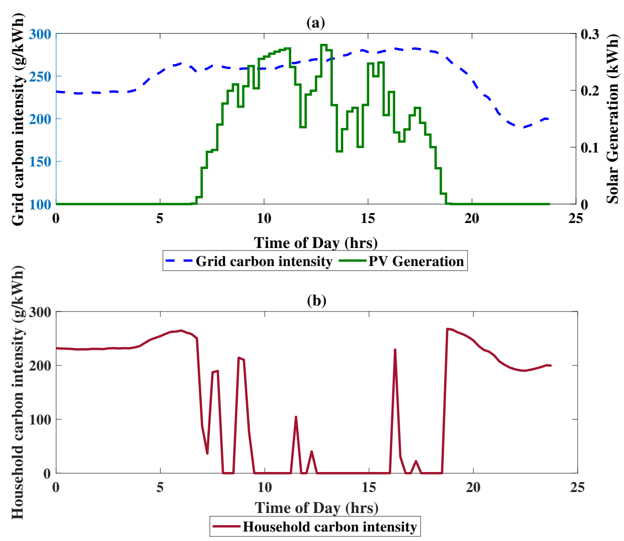

Fig. 1. (a) Typical grid electricity carbon intensity and household PV generation. (b) Calculated household carbon intensity from a typical day's electricity demand.

Fig. 1(b) shows there can be significant variations in household carbon intensity. The calculated household carbon intensity was then used to reschedule certain appliances to times of low carbon intensity.

B. Appliance Classification and Detection

Two wet appliances were considered: a washing machine and a dishwasher. These appliances were chosen as they are considered to be flexible in their starting time, resulting in minimal discomfort to the consumer. A two stage detection algorithm was developed that both detected and verified appliances in the historic demand data.

The first part of the algorithm detects appliances in the real demand data. Two search array signal templates were used, P_{wm} and P_{dw} for the washing machine and dishwasher, respectively. These template signals are shown in Fig. 2, representing a typical operating cycle for each appliance [14]. These power search array signals were used to detect similar appliance operating cycles in the historic electricity demand data.

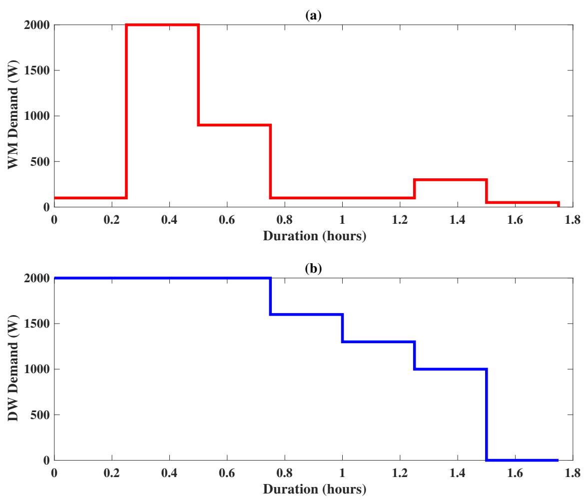

Fig. 2. Operating cycles for two wet appliances: (a) washing machine (WM), (b) dishwasher (DW) [14].

Appliances were detected using the Matlab function *findsignal* which finds the location of a segment in the demand data that best fits the search array, using a similarity search when compared to the search array signals P_{wm} or P_{dw}. The next stage is to verify the detected appliance by calculating the Pearson correlation coefficient, R using equation (5) and (6). This coefficient measures the strength between variables and in this case it measures the similarity of the detected appliance with the template signal. For each appliance that is detected, the verification coefficient is calculated using (5) and (6):

$$R = \frac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{\sqrt{[n\Sigma x^2 - (\Sigma x)^2][n\Sigma y^2 - (\Sigma x)^2]}} \quad (5)$$

$$x = P_a, y = \begin{cases} P_{wm} & \text{if } a = 1 \\ P_{dw} & \text{if } a = 2 \end{cases} \quad (6)$$

where P_{wm} and P_{dw} are the template search array signals for the washing machine and dishwasher respectively, given in Fig. 2, n is the number of data points, and P_a is the segment of the demand of the detected appliance. In (5) and (6), x represents the data points of the detected signal and y represents the template appliance data points. R must be greater than the given threshold value, α, to verify the appliance detection method as shown in (7). This value α can be increased or reduced which would result in the detection of more or fewer appliances. However, if this value is set too low, this could result in inaccurate detection. Equations (5) and (6) are subject to the following constraint:

$$R \geq \alpha, \quad 0 \leq \alpha \leq 1 \quad (7)$$

If an appliance is detected and verified, it is removed from the household electricity demand data. P_a is the power demand of the detected appliance, a, that was removed from the data at a time of detection t_d and a duration T. The detection of an appliance is subject to the following constraint shown in equation (8), which ensures that the operating power of the detected appliance does not exceed the original electricity demand at time t:

$$P_a^t < P_d^t, \quad t_0 \leq t \leq t_0 + T \quad (8)$$

where P_a^t represents the operating power cycle of the detected appliance at time t and P_L^t represents the historic demand power at time t.

C. Appliance Scheduling

The aim of the appliance scheduling is to minimise the carbon footprint of each detected appliance. The objective function (9) finds the minimum carbon emission of the operation of the appliance by choosing an optimal start time t_s:

$$C_{min} = min \sum_{t=t_s}^{t_s+T} \sum_{a=1}^{A} C_h^t P_a^t, \quad 0 \leq t_s \leq 24 - T \quad (9)$$

where t_s is the rescheduled start time, T is the duration of the appliance operation cycle, A is the number of rescheduled appliances, C_h^t is the household carbon intensity and P_a^t is the operating power of the detected appliance. In order to ensure the operation of the appliance does not exceed the length of the day, limits are applied to t_s shown in equation (9).

The original carbon footprint of the appliance without any rescheduling, $C_{original}$, is found using equation (10):

$$C_{original} = \sum_{t=t_d}^{t_d+T} \sum_{a=1}^{A} C_h^t P_a^t, \quad (10)$$

where t_d is the time of detection, T is the duration of the operating cycle, A is the total number of appliances. Using equation (11) it is possible to calculate the reduction in carbon emissions, ΔC, after the rescheduling process:

$$\Delta C = C_{original} - C_{min}. \quad (11)$$

D. Total Daily Carbon Emissions

If an appliance or multiple appliances are detected, the power demand from their detected operating cycle is removed from the daily demand at a time of detection, t_d. This is repeated for any other appliances that have been successfully detected and verified. The appliances are then rescheduled to minimise the total carbon emissions for the day using equation (9). For every possible start time t_s, for each detected appliance, the start time is rescheduled to produce a updated household power demand, P_n for the day. This new electricity demand is used to calculate a new household carbon intensity using equation (2) and the carbon emissions for the entire day using equation (12):

$$C_{total} = \sum_{t=0}^{24} C_h^t P_n^t. \tag{12}$$

This equation is repeated for every combination of rescheduled start time for each appliance. The rescheduling time at which the total carbon emission is at a minimum is recorded.

E. Proposed Algorithm

The following flow chart in Fig. 3 outlines the structure of the algorithm.

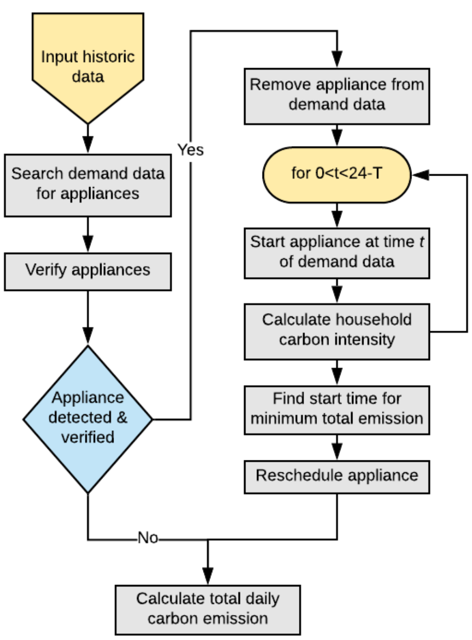

Fig. 3. Flowchart of proposed algorithm.

The algorithm's input data includes historic electricity demand data, P_d, PV generation data P_s, and template search array signals for a washing machine and a dishwasher, P_{wm} and P_{dw} respectively. The algorithm then searches the demand data for waveforms that are similar to the search array signals. These detected appliances are then verified using (5). The start time of the appliance is optimally selected to minimise the carbon emission of its operation as described in (9). The reduction in carbon emissions due to rescheduling is calculated using (11). Once the optimal start time is found, the daily demand data can be updated with the rescheduled appliance and the total carbon emission for the day is calculated using (12). The algorithm outputs the following results:

- Number of appliances detected,
- Time of appliance detection in original demand data,
- Original daily carbon emission,
- Carbon emission with appliance rescheduling,
- Time that appliance was rescheduled to.

III. Results and Discussion

A. Data Sources

Data for UK electricity generation and demand including generation type for 2018 is taken from GridWatch [12]. This source provides data at 5 minute intervals including the total demand and generation source. The household electricity demand data P_d^t at time, t, could be obtained from smart meters or energy monitors, such as Efergy technologies Engage system used in the SWIi project [15].

PV sources are considered as local generation in the dwellings as the PV generation can be directed towards a significant reduction in domestic carbon emissions. Solar generation is considered for a household PV system with an area of $10m^2$, system efficiency of 0.1 and a 40^o slope of panel. This outputs P_s^t which is the PV electricity generation at time t. To reduce carbon emission, this electricity generation will be used in real time to meet the household electricity demand (i.e. there is no household storage).

B. Simulation Set Up

The simulations were run for the duration of over half year for three different dwelling types. The data for each dwelling type included generation from a PV supply. The number of hourly divisions, t_p is taken to be 4 for each simulation (i.e., 15 minutes interval) and the accuracy threshold for detection, α, is taken to be 0.9. Appliances were only rescheduled if they were detected in the demand data and the correlation coefficient, R, is greater than the threshold value, α. Results were collected for the three dwellings in four different events to fully understand the effect of appliance scheduling. The four events are given in Table II.

TABLE II
SCENARIOS FOR SIMULATION RESULTS.

	PV supply	**Appliance Scheduling**
No Intervention (NI)	No	No
Scenario 1	No	Yes
Scenario 2	Yes	No
Scenario 3	Yes	Yes

Fig. 4 shows a typical sunny day where the rescheduling process has been carried out. It can be seen that two appliances have been rescheduled from approximately 18 hr and 22 hr to the middle of day where the household carbon intensity is

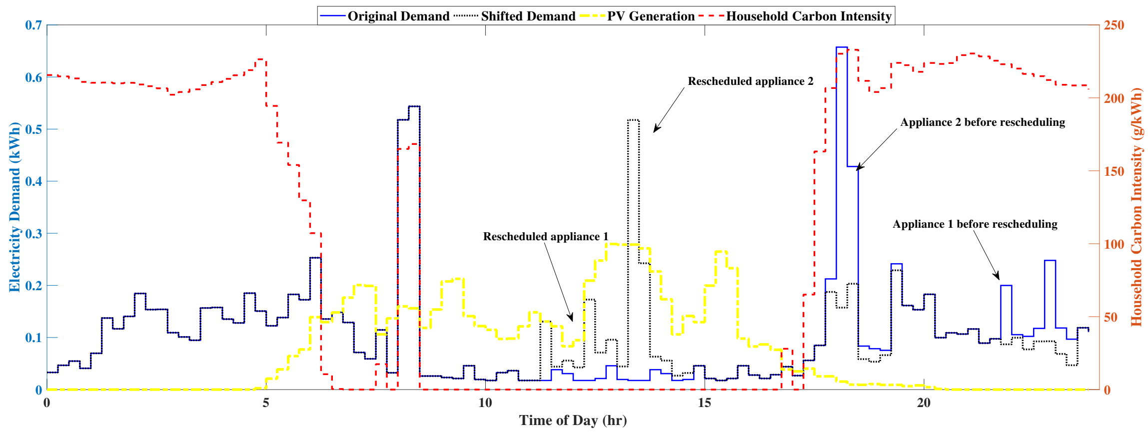

Fig. 4. A typical sunny day where two appliances have been rescheduled to minimise carbon emissions.

significantly reduced. This reduction in carbon intensity is due to the PV generation.

C. Results

1) Appliance Carbon Footprint: When considering only the carbon footprint of the appliance, before and after scheduling, it was found that all three scenarios outlined in Table II resulted in a reduction of carbon footprint. The results show that on average, a household with only grid supply can reduce the carbon footprint of a wet appliance by 23.9% by optimally scheduling its start time. This reduction marginally improved in scenario 2 (26.8%) where the appliance is not rescheduled but some of the household demand is met with PV generation. Finally, the greatest reduction in emissions is generated in scenario 3, where the household has a PV supply and the appliance start time is scheduled to minimise carbon footprint. This scenario resulted in a significant average carbon footprint reduction of 74.7% for the operation of an appliance.

TABLE III
AVERAGE REDUCTIONS IN CARBON FOOTPRINT OF APPLIANCES SUBJECT TO SCENARIOS 1-3.

	% Reduction in carbon emissions		
	Scenario 1	Scenario 2	Scenario 3
Dwelling Type 1	23.0	26.3	74.7
Dwelling Type 2	24.6	26.7	74.8
Dwelling Type 3	24.1	27.4	74.7
Average	23.9	26.8	74.7

Fig. 5(a) represents the carbon footprint reductions in scenario 1, where appliances are rescheduled in response to variations in grid carbon intensity only. In this case, very few appliances reduced their carbon footprint by more than 50%. Scenario 2, where appliances are not rescheduled and reductions are due to the availability of household PV generation, is shown in Fig. 5(b). Reductions were entirely due to the availability of PV generation and whether it aligned with the appliance operation. In this scenario, there was a significant share of the appliances that reduced their footprint by $0-10\%$. It is likely that this share is represented by the appliances

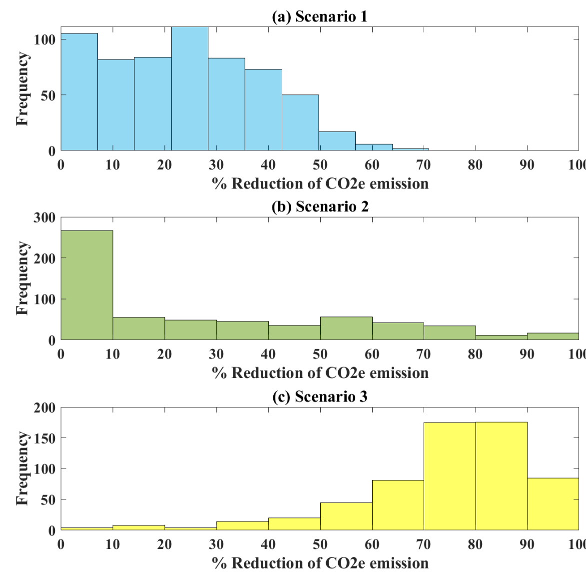

Fig. 5. Histogram showing the reduction in carbon footprint of rescheduled appliances for (a) scenario 1, (b) scenario 2 and (c) scenario 3, when compared to emissions with no intervention.

that were operated in the evening when the household carbon intensity is not significantly effected by the presence of a PV supply. However, some appliances had a reduction of over 80%. These greater reductions could represent the appliances that were operated during the day, where the availability of PV generation could dramatically reduce their carbon footprint. Scenario 3 demonstrates appliance scheduling in a household with electricity from the grid as well as a PV supply and is shown in Fig. 5(c). This scenario resulted in the majority of appliances reducing their footprint by over 60%. Fig. 5 shows that carbon footprint reductions can be made through the scheduling of the appliance both with and without a PV supply. The greatest reductions are achieved through optimally scheduling the start time of the appliance in a household with a PV supply (scenario 3).

Fig. 6 shows how the reductions in carbon footprint for the three scenarios varied for the dwelling type 1. Data is only included on the days when an appliance, or multiple appliances are detected and rescheduled. It can be seen that the reductions for scenarios 2 and 3 were significantly increased during the summer. This could be due to increased solar radiation providing an increased share of low carbon electricity.

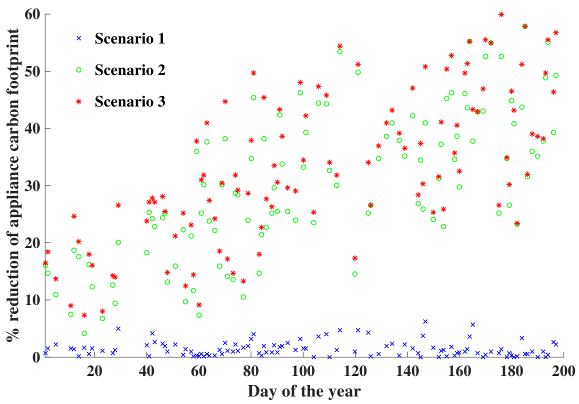

Fig. 6. Percentage decrease in carbon footprint of appliance usage in the case of scenarios 1-3.

2) Total carbon emissions from electricity: Table IV shows the predicted results of annual carbon emission. The total annual carbon emission is given for each scenario and the reduction in emission is found by subtracting the carbon emission from the No Intervention (NI) case.

TABLE IV
ANNUAL CARBON EMISSIONS FROM TOTAL ELECTRICITY DEMAND.

Dwelling Type	Type 1	Type 2	Type 3	Average
Scenario	**Carbon emissions (kg)**			
NI	1196.2	1175.7	1174.3	1182.1
1	1187.6	1166.4	1164.2	1172.8
2	900.4	880.7	880.7	887.3
3	882.8	863.5	861.3	869.2
	Reduction in emissions (kg)			
1	8.7	9.3	10.1	9.4
2	295.8	295.0	293.5	294.8
3	313.4	312.2	312.9	312.9
	% reduction			
1	0.7	0.8	0.9	0.8
2	24.7	25.1	25.0	24.9
3	26.2	26.6	26.7	26.5

When considering the total annual carbon emissions, each of the three scenarios resulted in a reduction in emissions. Across the three dwellings, on average 218 appliances were detected and rescheduled. These appliances accounts for 40% scheduling capability of wet appliances and wet appliances only make up for 15% of electricity consumption. For scenario 1, where demand was only met with grid electricity, the carbon emission reduction as a result of rescheduling 218 wet appliances was 0.8%. This reduction can be increased to 26.5% in scenario 3 where appliance scheduling is applied alongside generation from a PV supply.

IV. Conclusions

The results show that the scheduling of wet household appliances as part of a DSR scheme can lead to reductions in domestic carbon emissions. If there are no restrictions of operation time, the average reduction in carbon emissions for the operation cycle of a rescheduled appliance is 74.7% in a dwelling with both PV and grid supply, and 23.9% in a dwelling with only grid supply, respectively. These reductions were due to the variations of grid carbon intensity and the availability of PV generation. If more appliances were considered in the rescheduling process, this could lead to significant savings in carbon emissions.

V. Acknowledgments

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