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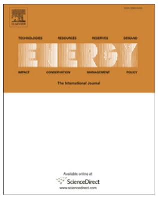

Impact of source variability on flexibility for demand response

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ABSTRACT

This paper assesses the quality of the services provided for demand response by analysing the results of experimental work activating flexible sources in buildings, while evaluating the impacts on occupant comfort and extending the dataset through aggregation, to quantify the uncertainty for multiple systems. Power and energy flexibility is an integral part of the solution to address the challenge of grid balancing with increased renewable generation integration. However, the variability of the provided flexibility, as measured by the stability and consistency of load reduction or increase, may vary widely. To address this, the concept of quality of flexibility is introduced and analysed through the results of experiments conducted at a case study building to activate three sources of flexibility: heat pumps, Air Handling Unit fans and battery storage. The results show that fan data exhibits low uncertainty, suitable for ancillary services, whereas heat pumps' volatility is large. Standard error for heat pumps was within the quality threshold of 10 %, appropriate for energy services. Aggregation of multiple systems through the creation of a semi-synthetic dataset decreased the uncertainty for hourly energy services to as low as 2 %. For all cases, the impact on occupant comfort was not found to be significant.

1. Introduction

1.1. Decarbonisation & electrification

Electrical power and energy flexibility is one of the key enablers of the distributed smart grid. Decarbonisation of the electricity grid, through increased renewable generation, coupled with electrification of transport, heating and industry has emerged globally as the preferred path to meeting EU, national and international renewable integration targets and the Paris Agreement [1]. Electrification is projected to double the quantity of electricity generation required by 2050 [2]. As a consequence, the quantity of renewable generation needed, even to maintain current integration levels, will be greater. In addition to current levels, renewable electricity integration targets are becoming increasingly ambitious. EU renewable generation targets have been revised upwards to 38 %–40 % of power generation from renewables by 2030 [3] and 90 % by 2050 [4], Denmark has a target of 100 % by 2030 [5] and California has set targets of 65 % by 2030 and 100 % by 2045 [6]. Balancing the grid while hosting such high levels of renewable generation is a challenge for grid operators [7]. One of the mechanisms used by grid operators to address this challenge is power and energy flexibility on the demand side [8].

1.2. Flexibility

Grid operators are preparing for a future smart grid with high levels of demand response integration [9] and regulators are starting to facilitate increasing participation by smaller buildings and sites [10]. Buildings in the US account for over 70 % of electrical energy consumption, with commercial buildings making up 36 % of total electricity usage [11]. The EU's planned Smart Readiness Indicator (SRI) is intended to quantify the energy flexibility capability of buildings and represent it in a meaningful way for stakeholders [12]. The International Energy Agency's (IEA) Energy in Building and Communities Annex 67 on Energy Flexible Buildings defined energy flexibility as the ability of a building or site to manage its demand and generation according to local climate conditions, user needs and grid requirements [13]. Buildings and sites can enter into contracts [14] with aggregators or grid operators to provide electrical flexibility as demand response or demand side services [15]. Grid operators then use this flexibility to manage the effects of

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intermittent renewable generation which causes issues with balancing supply and demand, hosting capacity at nodes with power restriction limits as well as frequency and voltage regulation [16]. In order to achieve the renewable integration targets set by regulators, increasing participation from more buildings and sites with deeper ranges of flexibility will be required [15].

Markets for flexibility are to be created in all EU countries as specified by the EU's Clean Energy Package, similar to the existing wholesale power generation pool markets [17]. Ireland already has such a market, known as DS3 [18]. In flexibility markets, aggregators bid into the market pool and the system operator chooses to accept or reject the bids. Programmes range from capacity markets, whereby participants are contracted for availability for a fixed fee with a minor activation payment, to energy services and ancillary services [18]. Ancillary services are fast demand response use cases, requiring response times in seconds or milliseconds [19]. While ancillary services are high value, the majority of building automation systems have response timeframes in minutes, and so are more suited to slower demand response programmes such as energy services in kWh, with lower financial rewards [20].

1.3. *Demand-side flexibility from customers*

Flexibility from customers is reached by combining power increases or decreases from multiple systems in buildings and sites, aggregating them together to offer electrical flexibility to aggregators or grid operators [13]. Building systems such as heat pumps [21], thermal storage [22], lighting [19], circulation pumps [23], Heating Ventilation and Air Conditioning (HVAC) Systems such as Air Handling Unit (AHU) fans [24] and Electric Vehicles (EVs) [25] have the capability to provide power and energy flexibility. The control and actuation of flexibility in the building or site systems is implemented using an ICT platform connected to existing building or site automation systems [24].

At the residential level [26], a number of underutilised sources of flexibility such as electrification of heating, primarily through heat pump technology [27,28] will bring opportunities for increased exploitation [29]. Commercial buildings are often already highly electrified and have a high potential for flexibility [19]. Small industrial sites such as water and wastewater treatment plants have a high flexibility potential as many processes can be shifted, controllable loads such as pumps are present, and if installed, cogeneration may provide small scale dispatchable, synchronous generation [30]. Transport electrification, perhaps the most high-profile electrification initiative, creates opportunities at the building or site level through the use of EV battery storage while the vehicle is charging [25], vehicle to grid flexibility whereby the battery in the vehicle may be discharged to the grid [31], as well as after the batteries have been removed from the vehicle, known as 2nd life batteries [32] which form part of the evolution to the circular economy. Electrification and system integration between heating and electrical energy networks will also bring greater need as well as opportunities for power and energy flexibility [15]. Such cross-energy vector system integration [33], for example between district heating and electricity, is being used by Denmark [34] as a means to achieve that country's 100 % target for renewable electricity consumption by 2030 [5].

Experimental work on the demand response potential of heating systems includes a study of 300 residential heat pumps which found significant load reductions of 40 %–65 % with an uncertainty of 7 % [35]. However, the response of the heat pumps to the demand response activation was to turn off, different to the more complex multi-compressor modulation of commercial heat pump systems. Residential electrical resistance heating was studies using on electrical meter data of 138 customers which developed and validated a data driven response model to predict baseline uncertainty for demand response. A standard deviation of between 9.5 % and 15 % of flexible load was calculated [36], however, electric resistance heating has a higher level of controllability than heat pumps and therefore the results may not be directly comparable. District heating meter data from 61 buildings in Copenhagen was used for typological categorisation of building types and the subsequent development of a numerical model for each archetype used in simulation of demand response. The results showed high potential peak reduction of up to 70 % using direct control of district heat supply water temperature, a different approach to thermostatically controlled loads [37]. As an alternative to experimental studies, Huang and Wu [38], used a detailed EnergyPlus white box model to generate a simplified battery-based models of buildings which were then used for demand response simulation. The detailed physics-based model was used to validate the demand response simulations of the simplified models, effectively creating a synthetic dataset for model testing and validation [38].

HVAC systems have been identified as a lower cost source of flexibility than other types of energy storage [39] and heat pumps are envisioned to be a key component in providing flexibility services in a highly electrified energy system. For example, commercial buildings cooling systems in the US are estimated to have the capability to provide up to 46 GW of flexibility for increased power consumption, known as positive or forced flexibility, and 40 GW for decreased power consumption, which is denoted negative or delayed flexibility [11]. Heat pumps in simulation studies were treated as thermostatically controlled loads [11]. Experiments with domestic refrigerators have shown some stability issues with demand response activation of thermostatically controlled loads [40]. However, solutions to deploy heat pump flexibility, coupled with additional installed storage and supplementary heating to provide a more stable load profile, have led to increases in the cost of the overall system by up to 12 % [41]. In addition, it has been found in Sweden that increasing electrification of the heating system using heat pumps is resulting in issues with overloading at to peak times, causing a gap between demand and supply [42], illustrating the need for reliable heat pump flexibility.

1.4. *Motivation*

As energy flexibility gains importance in guaranteeing the stability and efficiency of the energy grid, reliability of flexibility services becomes crucial [43]. Three main sources of uncertainty were identified in Ref. [44], namely renewable power, market price and load demand uncertainty, but the impact of flexible source uncertainty was not considered. The quality of flexibility provided by sources impacts the effectiveness of the service they provide to the grid, as uncertainty in demand response increases costs for grid operators [45]. If a source has a high average load reduction or increase capability [21] but with significant levels of variability [46], a noisy or unpredictable profile, this may intermittently negate the load reduction and work contra-productive to the grid impact measure it was contracted for [47]. Uncertainty of the provided demand response thereby increases the operational costs of energy systems [45] as grid operators require more backup systems [2]. A core part of this uncertainty is due to the level of controllability of loads providing demand response [44]. The preferred type of flexibility is a load reduction or increase which has a high level of controllability [49] is stable [48] and remains at the same electrical load level until the demand response event is completed.

Thermostatically controlled loads, which were assumed to have a smooth demand response profile in the US study [11], were shown to have high levels of variability in a field experiment using domestic refrigerators, even with aggregated loads [40]. Other simulation studies have assumed variance of 10 % of the predicted value [43] during demand response events. To quantify the actual impact of source variability, further experimental work is required to determine the effect on the quality of demand response of larger systems with thermostatically controlled loads, such as those in commercial buildings.

Occupant comfort is a key factor in widescale deployment of power and energy flexibility in buildings, as implementation is dependent on acceptability for building operators and occupants [24]. Consideration of user needs was specifically identified in the IEA Annex 67 definition for energy flexibility in buildings [13] and social acceptance was determined to be an important requirement for successful implementation in office buildings, in a study conducted under the Annex [50]. Measuring the effect on occupant comfort may be conducted through monitoring room temperatures and internal CO_2 concentrations, as well as complex approaches incorporating skin temperature sensing and active feedback polling [51]. However, active feedback polling has been shown to have high and variable non-response bias [52], leading to difficulties determining the actual level of dissatisfaction. While understanding the extent of the impact of flexibility events on occupant comfort is important, a cost-effective and minimally intrusive means of measurement using existing sensors and data, where possible, is preferred.

Data driven models such as in Ref. [53] require reliable training data from multiple previous flexibility activations to enable them to accurately predict system response during a demand response event. The lack of availability of appropriate high quality training data limits the effectiveness of these types of models [54]. Prior to contract negotiations between building or site operators and aggregators, few, if any, flexibility activations may occur, leading to the use of simulated data sets as an alternative [36]. A critical limitation identified for the use of simulated data sets is they do not consider the level of uncertainty which would be encountered in an experimental study [22]. This work aims to address that limitation through experimental results to determine the uncertainty in the flexibility of individual building systems and extending it to multiple systems, through the creation of aggregated dataset.

1.5. *Specific contribution & paper organisation*

The specific contribution of this paper is in introducing the concept of quality of flexibility, analysing the actual response of systems during a demand response event, thereby providing insights into real systems' behaviour, the level of controllability that is provided, impact on occupant comfort and quantification of the level of uncertainty in single and aggregated systems. These will enable greater integration of building systems in flexibility services, with deeper ranges, to meet renewable integration targets and achieve climate neutrality by 2050 [20]. Transfer of simulation work on heat pumps to the field has been recommended [27], as the findings of other experimental work, such as for circulation pump flexibility [23], bridge the knowledge gap between simulation and how real systems perform. This paper analyses the results of field experiments for flexibility activation conducted in a commercial case study building. Three flexible sources were present, AHU fans, a heat pump system and a battery storage system, but the analysis focuses on the HVAC systems, specifically the AHU fans and heat pump, as these are more critical for electrification of buildings [55]. Using measured results, this work highlights the sources which provided good quality, that is stable and consistent power load reduction, and those which have a more variable profile, the extent of which may not be evident in simulation studies. The impact of flexibility activation on occupant comfort is analysed through temperature and CO_2 data, coupled with monitoring the user-controlled set points before and after the flexibility event. To extend the results of the single system heat pump analysis to a more generalisable assessment, an approach used to extend limited experimental data [40], was adapted and used to create a semi-synthetic aggregated dataset to determine the uncertainty of multiple systems for participation in demand response services.

This paper is organised as follows: the experimental methodology is outlined in Section 2 defining quality, use cases and specifying methods of actuation. Section 3 describes the experimental set up consisting of the case study building, ICT platform, standard operating procedure and implementation to activate the sources of flexibility. Results and analysis of the flexibility activation are contained in Section 4 while the impact on occupant comfort is assessed in Section 5. Finally, Section 6 extends the analysis beyond a single system to create an aggregated dataset from uncertainty levels for multiple systems are assessed.

2. Experimental methodology

2.1. *Quality*

Quality of flexibility for demand response may be characterised in a number of ways. A variance of 10 % of predicted value for flexibility sources was used in an uncertainty simulation for an integrated energy system [43]. In an experimental study [40], the effectiveness of demand response activation of domestic refrigerators was assessed using the square root of the Integral Square Error (ISE) while also considering power ramp down and ramp up rates. Square roots of ISE varied between 26 W and 37 W, based on a requested value of 625 W for the combined loads, equivalent to 4 %–6 % error.

2.2. *Mathematical formulation*

The flexibility activation is represented in the mathematical formulation given below. Flexible system parameters for demand response events have been defined [56] to include the specific activation parameters such as power increase or decrease, but did not include uncertainty or error. The equations below explicitly include an error term to quantify the uncertainty for stakeholders committing to contracts for demand response. Forced or positive flexibility is represented in Equation (1) while delayed or negative flexibility is given in Equation (2).

$$\mathrm{F_f(t) = P_{max} - P(t) \pm \varepsilon(t)} \tag{1}$$

$$\mathrm{F_d(t) = P(t) - P_{lim}(t) \pm \varepsilon(t)} \tag{2}$$

whereby $F_f(t)$ is the available forced flexibility for the hourly time period t; P_{max} is the maximum electrical load of the system, in the case of the VRF heat pump system P_{max} is linked to the thermostatically controlled set points; $P(t)$ is the power at time t and ε is the error or uncertainty. $F_d(t)$ is the delayed flexibility at time t and $P_{lim}(t)$ is the permitted power limit reduction or constraint threshold. The quantities relating to flexibility formulation are represented on the power curve in Fig. 1.

In this paper, the stability and consistency of the load reduction provided by each flexible source was measured by the standard deviation and standard error of the data recorded during the demand response events. Based on the error levels from literature outlined in Section 2.1, quality thresholds are defined as error below 10 % considered acceptable with 4 %–6 % representing good quality flexibility. Assessment of the time series graph for each event was also used for quality analysis. Standard deviation is an

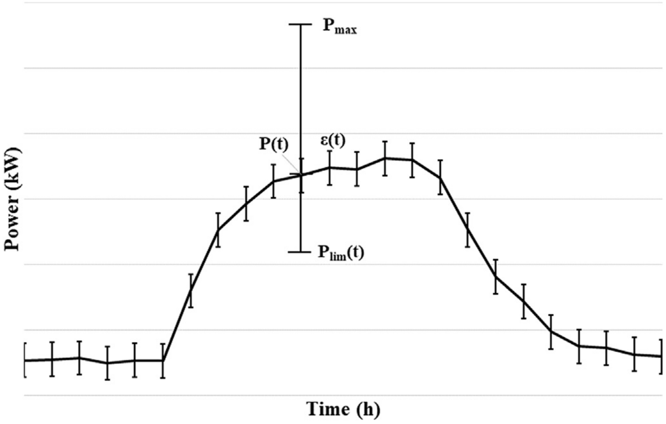

Fig. 1. Flexibility activation representation.

indication of the variability of the power fluctuations during the event, whereas standard error measures the sample mean compared with the population mean. For demand response use cases whereby the instantaneous load reduction is paramount, standard deviation is the most appropriate metric. However, for use cases where the average power reduction is the contracted value, such as in energy balancing services in kWh, standard error is the relevant measure of uncertainty.

2.3. Use cases

Two demand response use cases were selected, peak shaving and an intra-day request. Peak shaving is a price-based programme in which customers reduce grid import electricity between during periods of peak consumption. The most widely used demand response service globally, Ireland [18], the US [24], France [57] and China [58], among others, include peak shaving in their demand side services. Contracts are typically based on set time periods, known in some cases, over a year in advance. Peak shaving was emulated for the 4-h experiment.

An intra-day request is made in a market-based programme. It requires the building to respond to a grid request in the intra-day market within a short timeframe and is therefore more challenging than peak shaving. In Ireland this is implemented as Short Term Active Response (STAR) [18]. An intra-day request was emulated for the 1-h experiment.

2.4. Methods of actuation

2.4.1. Direct motor control

The type of actuation for the AHU fans was direct motor control using the Variable Speed Drive (VSD) installed to control the fan motor. Sometimes known as a Variable Frequency Drive (VFD) or inverter drive, the actuation input is a percentage change which varies the frequency of the electrical power to the fan motor. 100 % of motor output is equal to 50 Hz frequency, 80 % equal to 40 Hz, 50 % equal to 25 Hz and so forth. VSDs for the fans were installed externally to the motor and were controlled by the BMS. External installation of VSDs controlled by a BMS or Supervisory Control and Data Acquisition (SCADA) are common in commercial buildings and industrial applications [59]. Where control is by an external automation system such as BMS or SCADA, it is possible to implement direct motor control for demand response applications. Internal VSDs or inverter drives are widely used in heat pumps and chillers where the motors are controlled by the equipment's proprietary controller [60]. Inverter drives are used to control the compressor output by modifying the compressor motor frequency. In equipment where the controller is part of the manufacturer's internal controls, it is not possible for a third party to externally use direct motor control for demand response applications.

2.4.2. Set point control

Control of equipment using set points such as temperature, through Thermostatic Load Control [11], is convenient for whole building HVAC control, as one set point may be utilised to control the entire building [61]. Set point control [27] a) is easily accessible; b) minimises investment in additional equipment and c) takes user comfort considerations into account. In many HVAC systems, particularly residential heating systems, it may be the only control method available. When assessing whether systems are flexible using a Shedability, Controllability and Acceptability filter [24], set point control may pass the Acceptability criteria where direct motor control may not. Other examples of set point control include CO_2 concentration for indoor air quality in buildings, hot water temperature set point for Domestic Hot Water in buildings or level control set points in industrial applications.

2.5. Occupant comfort

As occupant comfort is central to the acceptability of demand response implementation, potential impacts on occupant comfort were measured during the experiments. Four specific metrics were used i) indoor air quality as measured by CO_2 concentrations in AHU return air; ii) variation in indoor air temperatures in internal rooms; iii) altering of user adjustable set points after the event for individual ceiling cassettes and iv) feedback from the building facility manager. The maximum CO_2 ppm limit for educational institutions in the UK is 1500 parts per million (ppm) [62], ASHRAE recommended guidelines specify of 700 ppm above outdoor levels of 300 ppm–500 ppm are equivalent to a range of 1000 ppm to 1200 ppm [63]. For the internal air quality to be deemed sufficient, concentrations must be below these thresholds. Monitoring of user adjustable set points is a low cost, unintrusive approach for measuring user discomfort or dissatisfaction with comfort conditions during the flexibility activation. It also has the advantage of minimising non-response bias found in active polling approaches. Feedback from the Facility Manager was sought after the event to ascertain if any complaints were received in relation to occupant comfort.

2.6. Multiple systems

To extend the analysis from a single building and understand the uncertainty of multiple systems, an aggregated dataset was created from measured building data. As heat pumps have been identified as particularly important for managing flexibility in buildings [42], the analysis focused on the VRF heat pump system. In addition, thermostatically controlled loads have a higher degree of uncertainty as they do not offer the same guarantee of load reduction as direct motor control. The approach for creating the aggregated dataset was adapted from a method used for thermostatically controlled loads in a residential study [40]. Multiple days data for the same systems were combined to produce a semi-synthetic dataset. For this work, the methodology was adapted to use normal operation data, rather than flexibility events, as a means to bridge the gap between simulation and experimental studies [29], focusing specifically on the VRF heat pump thermostatically controlled loads.

3. Experimental set-up

Flexible sources, consisting of AHU fans, a heat pump system, and a Lithium-ion battery system were activated in a case study building with photovoltaic (PV) on-site generation, in response to demand response requests. The experiments were conducted using an ICT platform, a standard operating procedure was put in place for liaison with the operators of the building and the OpenADR [64] protocol emulated demand response signals for specific use cases.

3.1. Case study building

The case study building was the Skills Academy for Sustainable Manufacturing and Innovation (SASMI) located in Sunderland, UK. It is a 5500 m^2 mixed-use commercial building consisting of seminar rooms, offices, workshops and catering facilities and has an Energy Performance Certificate rating of C. The building was chosen as it was a pilot site in the ELSA Horizon 2020 project [65]. It is representative of a typical commercial building and is not a highly optimised or close to NZEB building [66], as has been used for other flexibility research [67]. As part of the ELSA project, an ICT platform was installed, enabling activation of flexible sources at the building, including the ELSA 2nd life EV battery system.

The building peak power load was of the order of 140 kW and base load was between 20 and 40 kW. Flexible loads consisted of HVAC loads and storage. The HVAC loads were a Variable Refrigerant Flow (VRF) heat pump system and AHU fans. The VRF heat pump system is an air-to-air system which uses refrigerant as the transport fluid between the six external condensers and 35 ceiling mounted cassette units in the occupied spaces. During normal operation, users may change room temperature set points, but during the flexibility events, global temperature control was implemented using the ICT platform. The AHU fans were supply and return fans in four AHUs incorporating heat recovery heat exchangers. Fan speeds were fixed during commissioning of the building in the latter stages of construction, using VSDs. The AHUs were used in winter to provide ventilation and base load heating with the VRF heat pump system modifying temperatures to user preferences in individual rooms. In summer, the AHUs provided ventilation and comfort cooling needs were met by the VRF heat pump system. Storage consisted of an early prototype 2nd life EV Li-Ion battery system with an installed capacity of 48 kWh. A 50 kWp PV array provided on-site renewable generation.

3.2. ICT platform

An ICT platform installed at the building owners' facility was used to actuate the sources of flexibility during the experiment and record data. Aggregator or grid signals were emulated using an OpenADR protocol [64]. The ICT platform was accessed remotely, data was recorded and the control set points modified in the case study building's Building Management System (BMS). Earlier versions of the ICT platform were successfully deployed on previous projects managing power and energy at building [68] and district scale [69], prior to the platform being adapted for demand response implementation in the case study building where the experiments were conducted.

3.3. Standard operating procedure

Before proceeding with the experiments, permission was required from the case study building. A Standard Operating Procedure (SOP) was put in place to obtain explicit written permission to conduct the experiment from the building operator. The SOP outlined the proposed experiment, the systems required, any supervision requirements on-site and highlighted any potential impacts on occupants. The SOP was signed off by the facility manager for the building and the project contact for the pilot site.

3.4. Implementation

To activate the sources of flexibility in the building, set points of the loads and storage were adjusted using the ICT platform. PV output is not controllable but was monitored during the experiments using its electrical meter. The set points for the HVAC systems were determined from previous work documenting the results of a utility led demand response programme in 28 buildings using temperature set point as the control variable [61] and an experimental study on pre-cooling in two buildings [70] which achieved a 20 % electrical power reduction for HVAC systems. The AHU fan set point applied in this work was a 20 % fan speed reduction while maintaining CO_2 levels below acceptable indoor air quality limits, between 1000 ppm and 1500 ppm. The VRF heat pump system global set point was a 2 °C global temperature set point increase from 20 °C to 22 °C as the experiment was conducted during summer. The battery system set points were −36 kW for the 1-h event and −12 kW for the 4-h event. The 1-h set point is the maximum discharge rate of the battery system whereas the 4-h set point was selected to discharge the maximum battery capacity over the duration of the 4-h event.

4. Results & analysis

Results from the two experiments are shown in Fig. 2 for the 4-h flexibility event and Fig. 4 for the 1-h flexibility event. Detail of the results for the HVAC systems, AHU fans and VRF heat pump are shown in Fig. 3 for the 4-h event and Fig. 5 for the 1-h event. The measurement values, standard deviations and standard errors for the results are presented in Table 1 for the 4-h event and Table 2 for the 1-h event. Mean flexibility is measured in kW power reduction and expressed as a percentage of peak building load. The peak building load for the case study building was 140 kW. For example, for the HVAC fans, the mean flexibility of 4.3 kW divided by 140 kW peak load is equal to a 3 % reduction in building peak load. Standard deviation is an indication of the variability of the power fluctuations during the event, whereas standard error measures the sample mean compared with the population mean. For demand response use cases whereby the instantaneous load reduction is paramount, standard deviation is the most appropriate metric. However, for use cases where the average power reduction is the contracted value, such as in energy balancing services, standard error is the relevant measure of uncertainty. The results show the actual electrical measurements taken at the sub-meters for each system and the main building meter for grid import.

The results of the 4-h experiment are shown in Fig. 2. The demand response event took place between 11:00 and 15:00 h. While the standard deviation of all sources, with the exception of the HVAC AHU fans, was significantly high - between 32 % and 55 %, the standard error was 10 % or less for all sources.

Detail of the AHU fans and VRF heat pump electrical load profiles during the 4-h demand response event are shown in Fig. 3. From the AHU fans results, shown in grey on the left, the drop in electrical consumption is evident at 11:00 and maintains a steady and consistent load reduction for the duration of the event. The VRF heat pump load profile on the other hand shows significant volatility during the event. The initial load reduction is much higher than the AHU fans, of the order of 20 kW as compared with 4 kW for the fans, but the system load fluctuates considerably after this.

The results of the 1-h experiment are shown in Fig. 4. The demand response event took place between 11:00 and 12:00 noon.

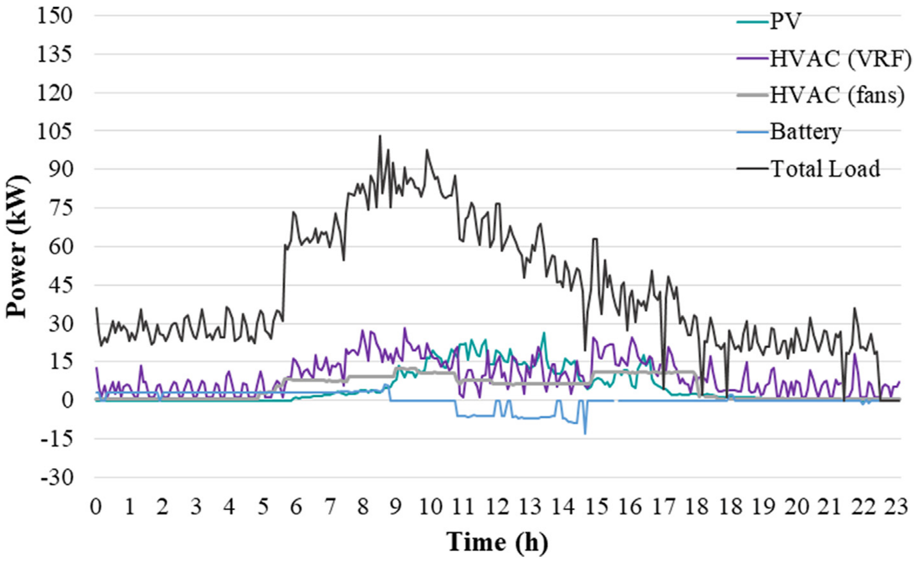

Fig. 2. Results Four-hour Flexibility Event. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

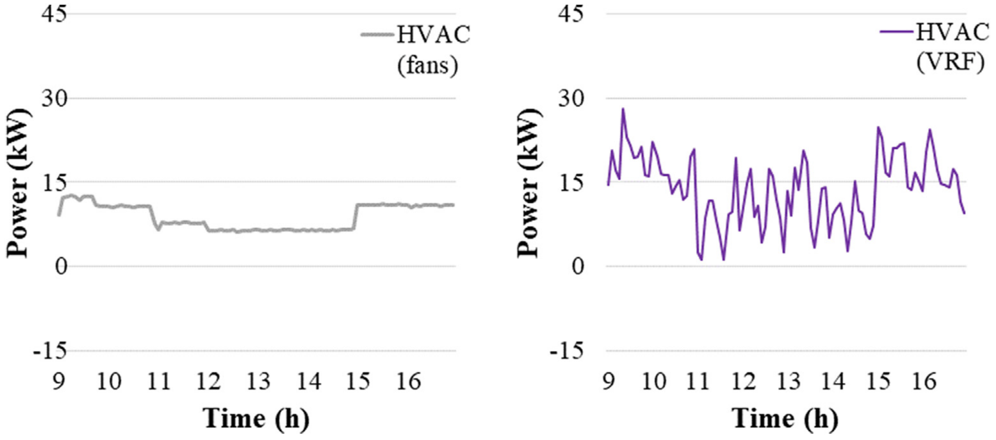

Fig. 3. HVAC Systems AHU Fans (on left) and VRF (on right) Detail, Four-hour event. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Detail of the AHU fans and VRF heat pump electrical load profiles during the 1-h demand response event are shown in Fig. 5. The AHU fans load on the left of the figure again show a stable load reduction of 4 kW during the event whereas the VRF heat pump system, despite an initial large drop of approximately 14 kW, fluctuations in the electrical load caused the mean load reduction during the event to reduce to 6 kW. The PV output decreased during the event due to a temporary decrease in solar radiation e.g. a cloud passing over the array. Comparing the results in Fig. 3 for the 4-h event with the results in Fig. 5 for the 1-h event, system behaviour was similar in both experiments as the AHU fans exhibited a stable and consistent load reduction during both events whereas the VRF system electrical load was more volatile.

As the dataset for the 1-h experiment was smaller than the 4-h experiment, both the standard deviation and standard error of almost all sources, was increased. In the case of the HVAC VRF heat pump system, the standard deviation was 86 %, indicating extremely high levels of volatility. However, the standard deviation and standard error of the HVAC AHU fans was very similar, both experiments having 9 % standard deviation and standard error between 2 % and 3 %.

4.1. HVAC — AHU fans

Of the HVAC loads, the AHU fan flexibility provided a stable and consistent load reduction as shown in Figs. 3 and 5. The quantity of load reduction was 3 % of building peak load which was equivalent to approximately 4 kW for both the 4-h and 1-h events. The standard deviation of the load reduction data was between 0.4 and 0.6 kW, demonstrating the least volatility of all the flexible sources. Expressing the standard deviation as a percentage of the mean power reductions of 4.3 kW for the 4-h event and 4.4 kW for the 1-h event respectively, standard deviation was equivalent to 9 % of the measurement value for both events. Based on the quality thresholds from literature outlined in Section 2.1, of between 4 % and 10 % variance, this may be regarded as low source variability, indicating suitability for fast demand response use cases. The standard error is also low at between 2 % and 3 %, meaning the HVAC AHU fans also show good suitability for energy services use cases.

4.2. HVAC - VRF heat pump system

The HVAC VRF heat pump system exhibited significant volatility

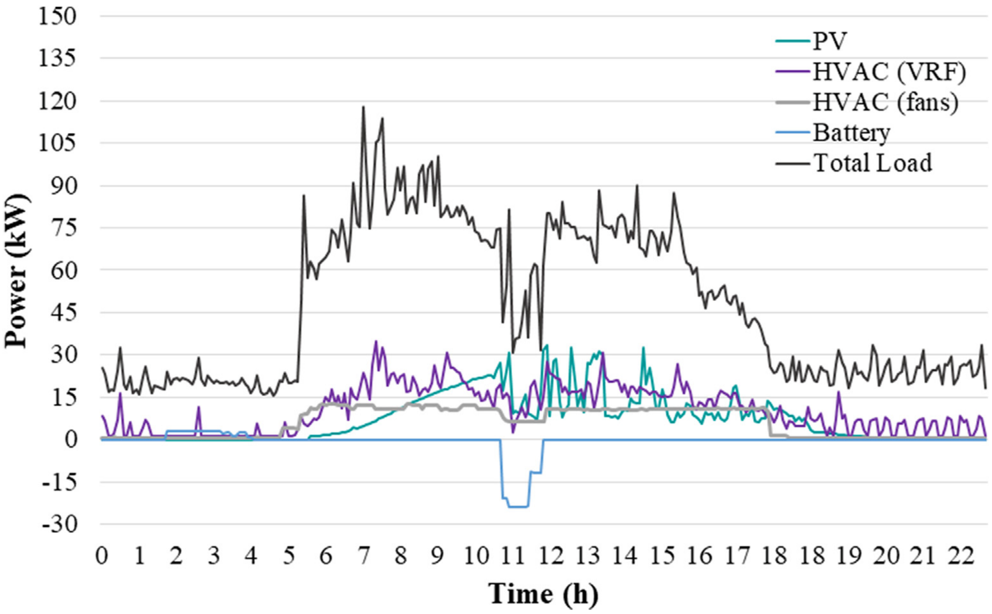

Fig. 4. Results One-hour Flexibility Event. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

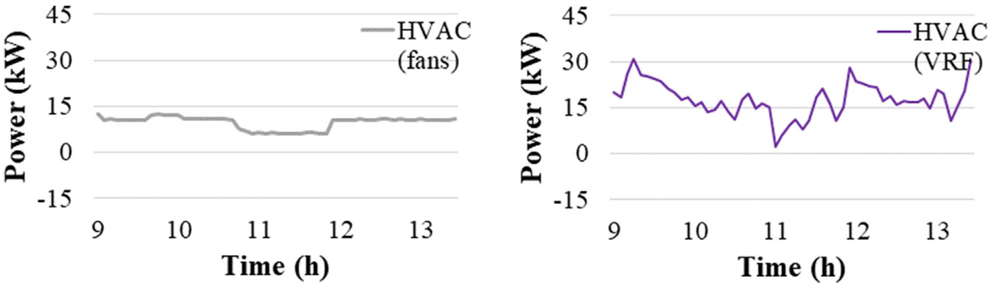

Fig. 5. HVAC Systems AHU Fans (on left) and VRF (on right) Detail, One-hour event. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Power reduction & standard deviation of flexible sources: Four-hour event.

Flexible Source	Flexibility (%)	Mean Flexibility (kW)	Standard Deviation (kW)	Standard Deviation (%)	Standard Error (kW)	Standard Error (%)
HVAC (fans)	3 %	4.3	0.6	9 %	0.1	2 %
HVAC (VRF)	5 %	7.4	5.1	51 %	0.7	10 %
Battery Storage	4 %	5.4	4.8	55 %	0.4	8 %

Table 2
Power reduction & standard deviation of flexible sources: One-hour event.

Flexible Source	Flexibility (%)	Mean Flexibility (kW)	Standard Deviation (kW)	Standard Deviation (%)	Standard Error (kW)	Standard Error (%)
HVAC (fans)	3 %	4.4	0.4	9 %	0.1	3 %
HVAC (VRF)	4 %	6.0	5.2	86 %	1.4	23 %
Battery Storage	14 %	19.7	5.6	28 %	2.0	10 %

during both flexibility events as shown in Figs. 3 and 5. The VRF system provides heating and cooling for the building and is strongly coupled to building physics and floor area. Building peak load reduction of 4 %–5 % was achieved, equivalent to 6.0 kW–7.4 kW. Standard deviation of 5.1 kW–5.2 kW indicates a high level of variability in the power reduction data, between 51 % and 86 % of measured value, meaning the VRF heat pump system does not demonstrate suitability for ancillary services type use cases. The standard error, however, was much lower for the 4-h event at 10 %, within the quality thresholds from literature, but was 23 % for the 1-h event. This points to suitability for energy services in kWh, particularly longer demand response events, but further analysis of the behaviour of multiple systems is required.

While the VRF heat pump system may have provided a deeper range of flexibility and a higher average load reduction than the AHU fans, it exhibited more volatility during the events. The volatility in the load reduction is due to compressors in the external condensers ramping up and down. To achieve a similar stability of load reduction as the AHU fan, one option would be to engage with system manufacturers to control the load at the compressor level using direct motor control and not through a temperature set point. Another option may be the use of predictive controllers at the BMS level using techniques such as Model Predictive Control (MPC) [27]. However, even with MPC, the compressor sequencing and control logic implemented by the manufacturer within the external condensers may still result in some volatility. For other types of heat pumps which utilise water as the working fluid, e.g. air-to-water or ground source water-to-water heat pumps, an appropriately sized thermal storage buffer tank may reduce volatility [54] but has been shown to add cost [22]. Water coupled heat pumps are more common in residential applications [26].

4.3. Battery storage

Discharging the battery storage system reduced the peak load by 4 % for the 4-h event and 11 % for the 1-h event. However, standard deviations were high, between 28 % and 89 % of the measured values. The stability of the discharge was not as smooth as would be expected from a Li-Ion battery system, however, this was due to the early prototype nature of the 2nd life EV battery system and its associated controllers. The battery system technology was at TRL 4 and research was being conducted on the system to bring it to TRL 5/6 as part of the ELSA Horizon 2020 project [65]. At TRL 9 this technology should provide a stable discharge.

Battery storage is an attractive source of flexibility as it provides almost instantaneous control of load increase or decrease [71]. When the 2nd life EV battery system is fully mature it should also exhibit the stability typically seen in commercial Li-Ion battery systems [72]. However, unlike HVAC systems, battery systems are installed in addition to existing building systems and so involve an investment by the building or site operator, specifically in battery system technology. Battery coupled PV installations are becoming increasingly common [73]. The utilisation of such a system may be beneficial for balancing unexpected reductions in PV output [74], as occurred during the 1-h event. This may be achieved through the implementation of a PV power smoothing demand response use case [75]. While financial payments from the provision of demand response services would need to be of a sufficient level to justify the installation cost of a dedicated battery system, the occasional use of a PV coupled battery system for flexibility applications may be more cost effective [76].

5. Occupant comfort

To evaluate any impacts on occupant comfort, CO_2 and indoor air temperature were monitored during the experiments. Sensors for relative humidity were not installed in the building. Monitoring of the user adjustable set points before and after the event was used as a low cost, unbiased and unintrusive approach for measuring user discomfort or dissatisfaction with comfort conditions during the flexibility activation. In addition, feedback from the Facility Manager, as per the Standard Operating Procedure outlined in Section 3.3, indicated that no negative feedback or complaints were received from occupants during the flexibility events.

5.1. CO2 monitoring

CO_2 levels were monitored as a measure of indoor air quality during the two events and results are shown in Fig. 6. A return air sensor in each AHU recorded the CO_2 concentration in parts per million (ppm). The return air to the AHU has higher levels of CO_2 than room air. Room air is a mix of fresh and recirculated air while the return air is the stale air extracted from the occupied spaces. While the maximum limit for educational institutions in the UK is 1500 ppm [62], ASHRAE recommended guidelines of 700 ppm above outdoor levels of 300 ppm–500 ppm are equivalent to a range of 1000 ppm to 1200 ppm [59]. From the graphs in Fig. 6 it can be seen that all of the AHU return air measurements were well below even the most stringent limit of 1000 ppm. One sensor, in AHU-5, was malfunctioning and has been removed from the dataset. Data from AHU-1, AHU-2 and AHU-3 sensors were between 400 ppm and 600 ppm, significantly below the recommended limits. It would be of interest to investigate in future if ventilation rates much higher than required by CO_2 thresholds are typical for commercial buildings, or unique to this case. As the VSD set points were fixed at commissioning stage, they may be optimal for winter operation but not for summer. Conversely, the high ventilation rates in summer may be providing an element of ‘passive’ cooling, a more energy efficient practice than refrigeration-based cooling. The low CO_2 levels may provide scope for improving the energy efficiency of normal building operation, outside of flexibility events. However, it is worth noting that the use of a CO_2 based varying set point for fan speed would need to be overridden by direct VSD control during a flexibility event.

5.2. Temperature Monitoring

The indoor air temperature in rooms with VRF heating and cooling were monitored to determine if there were any impacts on occupant comfort due to overheating. As can be seen in Fig. 7, two of the 35 rooms experienced spikes in temperatures during the 4-h event. As the number of rooms which experienced higher temperatures was low, and temperatures did not remain consistently high during the 4-h event, these intermittent higher temperatures may have been due to factors unrelated to the demand response activation. The mean temperature during the 4-h event, increased slightly, of the order of 0.5 °C, but remained well below the 22 °C set point. During the 1-h event, the mean temperature also increased slightly, between 0.5 °C and 1.0 °C, again remaining well below the set point, and no significant adverse temperature increases were recorded in any individual rooms.

5.3. User adjustable set point monitoring

Monitoring of the temperature set points, which reverted to individual user control after the demand response events, was also conducted and the results are shown in Fig. 8. Global temperature control was implemented using the ICT platform during the event to override individual temperature set points. If users experienced discomfort during the events, it would be expected that they would manually decrease the room temperature set point after the event. The experiments were conducted during summer, therefore cooling was in operation. As can be seen from the graphs in Fig. 8, users did not appear to modify set points, as those after the event are very similar to set points before the event. This would indicate that occupant comfort was not negatively impacted by the flexibility events, which is surprising. The set points for the HVAC systems were based on previous values used in literature, therefore, there may be scope for more significant load reductions to provide deeper ranges during flexibility events.

6. Multiple systems

To gain a more holistic understanding of the impact of multiple system behaviour, beyond the individual systems evaluated in the earlier parts of this paper, an aggregated dataset was created from

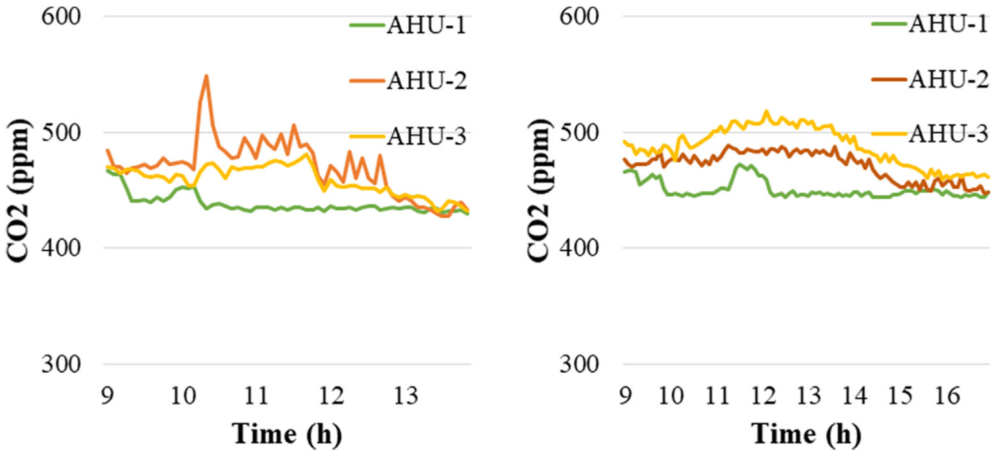

Fig. 6. Indoor Air Quality Monitoring, Four-hour Event (on left), One-hour Event (on right) with CO_2 limit shown at top of graphs. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

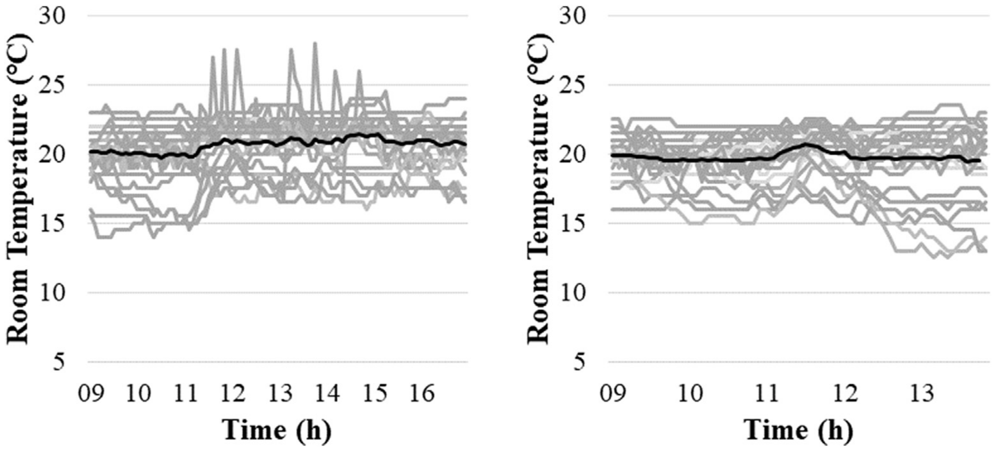

Fig. 7. Temperature Monitoring, Four-hour Event (on left), One-hour Event (on right) with mean highlighted in black.

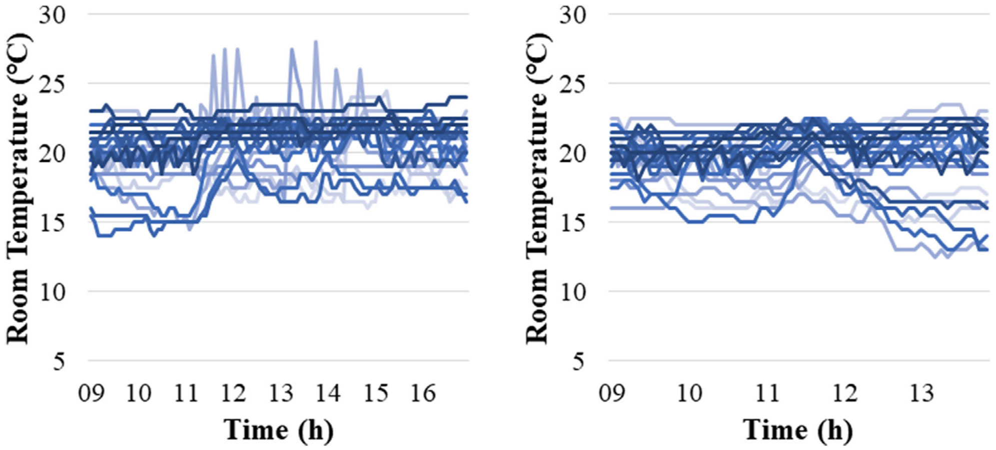

Fig. 8. Room Temperature Set Points, Four-hour Event (on left), One-hour Event (on right).

measured building data. The approach was based on the method used for thermostatically controlled loads in a residential study [40] whereby multiple days data for the same systems were combined to produce an aggregated dataset. This approach was adapted to use normal operation data, rather than flexibility events and focus specifically on the VRF heat pump thermostatically controlled loads, as they exhibited the most significant source variability. The data was then analysed to understand a) how the uncertainty of multiple heat pump systems differs from that of individual systems through analysis of aggregated systems; and b) the impact of

Table 3
Uncertainty of hourly aggregated VRF heat pump load.

Time (h)	Mean (kW)	Standard Deviation (kW)	Standard Deviation (%)	Standard Error (kW)	Standard Error (%)
7	12.6	4.5	36 %	0.3	2 %
8	14.6	4.6	31 %	0.3	2 %
9	16.3	5.4	33 %	0.3	2 %
10	16.8	5.4	32 %	0.3	2 %
11	17.4	5.4	31 %	0.3	2 %
12	17.3	5.4	32 %	0.3	2 %
13	18.1	5.6	31 %	0.4	2 %
14	17.9	5.4	30 %	0.3	2 %
15	16.6	6.0	36 %	0.4	2 %
16	12.6	5.7	45 %	0.4	3 %
17	9.0	4.9	54 %	0.3	3 %
18	7.2	4.4	61 %	0.3	4 %

uncertainty on performance versus predicted flexibility for contract commitments between individual building operators and aggregators. Uncertainty was assessed using standard deviation and standard error.

6.1. Aggregated dataset

Reliable data for training data driven or numerical models for flexibility depends on the available data for previous flexibility events [53], for either forced or delayed flexibility, as outlined in Section 1.4. This data is typically limited, for example before a building engages in contracts for demand response, there may only have been a few functional tests, if any, performed to verify the flexibility potential of the proposed system, with simulated data sets being uses as an alternative [40]. To overcome this limitation, an aggregated dataset was created by combining VRF heat pump electrical load data for multiple days with similar outside air temperature profiles and building operating hours. In total, 21 days data was aggregated, representing an installed heat pump capacity of 735 kW, 21 buildings or the equivalent of 126 individual VRF external condensers.

6.2. Results & analysis

The standard deviation and standard error of the aggregated dataset were calculated for 1-h intervals, a common timeframe for energy services in demand response balancing markets. From the results presented in Table 3, during building operating hours the standard deviation varied between 30 % and 61 % whereas the standard error is much lower at between 2 % and 4 %. Although the standard deviation is relatively high, quantifying the observed volatility in Fig. 9, and making the system unsuitable for fast demand response services, the low standard error means the variation of the mean during the 1-h period is relatively stable. Therefore, the low standard error indicates good suitability of thermostatically controlled loads for energy services, where the contracted services is for an average power reduction or increase over a specified time period and payment is per kWh.

6.3. Limitations

This work is primarily an experimental study of a single building and therefore the generalisability of some of the results are limited. The results for individual systems are subject to the actual flexibility event and the type of options and their ranges available at the specific building. The advantage of simulation studies is their ability to analyse a variety of building topologies, systems and climate conditions. However, to replicate these in experimental work would be extremely resource intensive and cost prohibitive, therefore, inferences from existing building data or a combination of experimental and simulation studies will be required to address this gap.

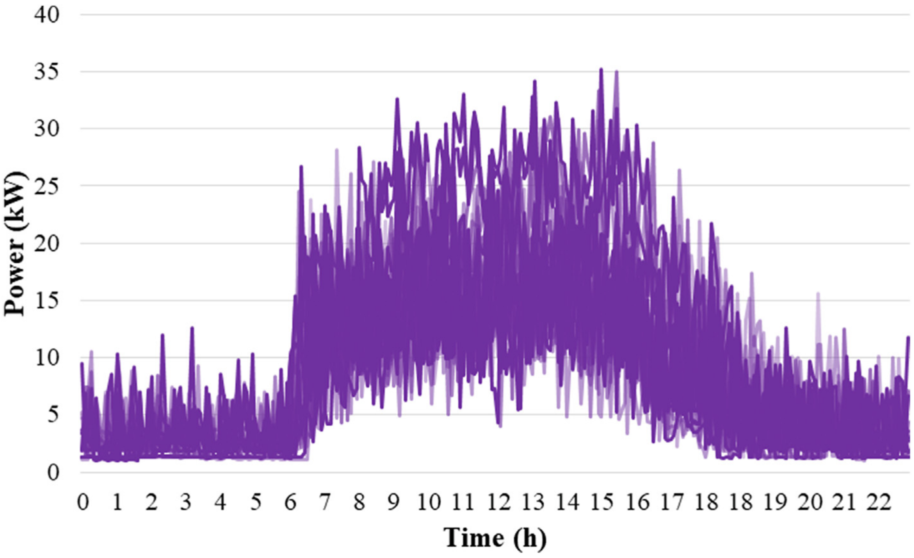

Fig. 9. VRF heat pump aggregated dataset.

While error quantification using statistical techniques has been presented, further insights into flexibility uncertainty may be gained from the development of a detailed uncertainty quantification, generalisable for a wide variety of building systems under a range of conditions such as varying weather and fluctuating demand in the building.

Aggregation of multiple heat pump systems has been shown to reduce the standard error for energy services, however, exploration of the challenges of aggregation at scale, up to thousands of buildings with a more diverse range of flexible sources would be worthwhile.

This work has highlighted the impact of source variability on the reliability of flexibility services, but the limitations outlined here illustrate the need for further research to understand the operational challenges and resilience of energy flexible buildings and communities.

7. Conclusions

Quality of flexibility was introduced as a concept and quantified using error and variance thresholds in previously published literature, providing a range between 4 % and 10 %. Experimental results from the activation of different flexible sources: heat pumps, fans and battery storage, illustrated the characteristics of the load reduction from each source. An assessment was conducted of the variability of the flexibility provided, analysing the stability and consistency of load reduction during the demand response events using time series and statistical approaches. The use of direct motor control for the AHU fans achieved the most stable load reduction of all the flexible systems, as quantified by the low standard deviation of 9 % in the recorded data, standard error of between 2 % and 3 % as exhibited by a steady load reduction in the time series graph. By directly controlling the motor speed and frequency, variation in load reduction during the flexibility event was minimised while simultaneously maintaining CO_2 concentrations below recommended limits. With a standard deviation below the 10 % quality threshold, this indicates suitability for more financially rewarding fast demand response services such as ancillary services. Heat pumps provided a deeper range of flexibility but exhibited more volatility. Electrification of heating systems, primarily through heat pumps, will mean that the quality of flexibility provided by these systems will become more critical. The standard deviation of the heat pump systems was high, up to 86 % of measured value in some cases, indicating the systems are not suitable for fast demand response services. However, the standard error of the heat pump systems was much lower, at 10 % for the 4-h event, indicating suitability for kWh energy services, particularly for longer demand response events.

Occupant comfort was not adversely impacted by the flexibility event, based on CO_2 and temperature data coupled with user-controlled set point monitoring, a result which was unexpected. This may indicate further scope for deeper load reductions during flexibility events than previously indicated in literature, a key finding, as deeper ranges will be required to meet renewable integration targets. In addition, there may be potential for increased energy efficiency gains during normal building operation, particularly for ventilation, as the measured CO_2 levels were significantly below required thresholds.

Creation of an aggregated dataset enabled analysis of multiple days data and was used to emulate the behaviour of 126 heat pump external condensers or 21 buildings. The analysis determined that the uncertainty of the heat pump flexibility decreased significantly as standard error reduced to between 2 % and 4 %. This reduces the uncertainty for stakeholders committing to energy-based demand response programmes.

Future work may include more experimental studies to understand if the occupant comfort results are replicable in other buildings, or are unique to this case; development of more advanced numerical techniques to overcome insufficient training data for flexibility performance, such as detailed mathematical models for uncertainty quantification; further experiments to determine the limits of user acceptability based on the lack of change to user adjustable set points identified in this work; investigation of advanced methods to enable direct compressor control in heat pumps and the creation of more smart ready building energy management systems with faster response times to enable ancillary services at the building level. Studies on the aggregation of building data from multiple buildings to extend it to communities are planned in IEA Annex 82 ‘Energy Flexible Buildings Towards Resilient Low Carbon Energy Systems’ aimed at addressing the challenges and opportunities facing the widespread implementation of energy flexibility as an enabler for grid decarbonisation.

Credit author statement

Sarah O'Connell: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft. Glenn Reynders: Writing – review & editing. Marcus M. Keane: Supervision.

Sarah O'Connell: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft. Glenn Reynders: Writing – review & editing. Marcus M. Keane: Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Nomenclature

AHU	Air Handling Unit
API	Application Programming Interface
BMS	Building Management Systems
COP	Coefficient of Performance
DR	Demand Response
EV	Electric Vehicle
HVAC	Heating, Ventilation and Air Conditioning
ISE	Integral Square Error
MPC	Model Predictive Control
PV	Photovoltaic
SASMI	Skills Academy for Sustainable Manufacturing and Innovation
SCADA	Supervisory Control and Data Acquisition
SOP	Standard Operating Procedure
TRL	Technology Readiness Levels

VRF	Variable Refrigerant Flow
VSD	Variable Speed Drive
VFD	Variable Frequency Drive

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