Benefits of smart control of hybrid heat pumps: an analysis of field trial data

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Abstract

Smart hybrid heat pumps have the capability to perform smart switching between electricity and gas by employing a fully-optimized control technology with predictive demand-side management to automatically use the most cost-effective heating mode across time. This enables a mechanism for delivering flexible demand-side response in a domestic setting. This paper conducts a comprehensive analysis of the fine-grained data collected during the world's first sizable field trial of smart hybrid heat pumps to present the benefits of the smart control technology. More specifically, a novel flexibility quantification framework is proposed to estimate the capability of heat pump demand shifting based on preheating. Within the proposed framework, accurate estimation of baseline heat demand during the days with interventions is fundamentally critical for understanding the effectiveness of smart control. Furthermore, diversity of heat pump demand is quantified across different numbers of households as an important input into electricity distribution network planning. Finally, the observed values of the Coefficient of Performance (COP) have been analyzed to demonstrate that the smart control can optimize the heat pump operation while taking into account a variety of parameters including the heat pump output water temperature, therefore delivering higher average COP values by maximizing the operating efficiency of the heat pump. Finally, the results of the whole-system assessment of smart hybrid heat pumps demonstrate that the system value of smart control is between 2.1 and 5.3£bn/year.

Keywords: Demand response, hybrid heat pump, power system economics, flexibility quantification, smart control technology.

1. Introduction

Electrification of the heat sector, as part of the overall effort to decarbonize energy supply, is expected to entail the replacement of fossil fuel-based heating systems with those based on electric heat pumps (EHPs), thus reducing the carbon footprint of the heating sector through supplying it with less carbon-intensive electricity as a result of deploying renewable, nuclear and other low-carbon generation technologies [1]. Widespread adoption of EHPs may however lead to significant increases in peak electricity demand as their peak utilization generally coincides with the timing of non-heating peak demand in current UK power system, with consequences on different segments of the electricity system. Therefore, a large penetration of EHPs is likely to trigger significant investment in peaking generation capacity as well as reinforcements in transmission and distribution grids to enable them to cope with additional demand [2].

Hybrid Heat Pumps (HHPs) combine a low-temperature EHP with a gas boiler. The advantage of the dual-fuel capability of HHPs is that these can switch between fuel sources (i.e. to use the boiler, heat pump (HP) or both to meet the heat demand) based on the efficiency of the system under current circumstances (e.g. outdoor temperature, flow temperature, etc.) or prices of gas/electricity [3]. Another advantage of HHP systems for the user is that the rating of HPs (which is the more costly component of the hybrid system) can be lower as the gas boiler can be used to top up heat production. The authors in [4] reviewed major HHP systems suitable for application with various heat sources, demonstrating that HHP systems can improve the efficiency of thermal heat, extend the application of EHP and markedly reduce carbon emission. Reference [5] compares the overall investment costs of different types of hybrid heating technologies in a combined power-residential heat system, concluding that HHP sourced by a combination of electricity and gas can drive the greatest economic benefits over the other types of hybrid heaters. The authors in [6] further investigated the decomposed benefits of large-scale deployment of HHP across different sectors of the multi-energy system, indicating that HHP has the potential to pave a cost-effective pathway to a low-carbon future energy system. Numerical studies on the application of HHP systems in residential buildings have been performed in [7], pointing out that HHP can provide an effective solution to the concerns of the over-dimension of EHP.

Although HHP can provide considerable customer value through demand flexibility, standard HHP installations are still not controlled in a fully-optimized manner that balances the needs of the consumer and the energy networks [8]. To tackle this challenge, a smart control technology for hybrid heat pumps has been developed, incorporating predictive demand-side management and proactive consumer engagement, to enable switching between electricity and gas to use the most cost-effective heating mode at any time in a fully-automatic fashion [9]. The proposed predictive demand control (PDC) algorithm aims to learn the thermal characteristics of the house for building an ad-hoc model of the house and heating system. The smart control strategy is employed to rapidly warm up the property by activating the gas boiler with the HP providing temperature maintenance and a 'baseload' when a fully warm house is not essential [9]. Smart hybrid heat pumps (SHHPs) are further able to employ preheating strategies that redistribute heat demand across time in order to minimize consumer cost, improve utilization of low-carbon generation and enhance the overall energy efficiency of the heating system. In [10], the authors investigated preheating through building thermal capacitance to reduce the operational costs associated with maintaining comfort conditions, indicating that energy costs and electricity peak demand can be dramatically reduced by using preheating. In addition, the smart control technology of HHPs can provide balancing services (frequency response and reserve services) and improve the integration of variable renewables while reducing the need for higher capital cost of firm low-carbon generation such as nuclear or CCS.

A key benefit of SHHPs lies in the demand flexibility based on switching between electricity and gas, which can be used to reduce peak electricity demand and the corresponding investment in additional generation and network reinforcement. In general, the flexibility provided by heating systems is represented as the deviation of the power consumption of the heating device from its profile under normal operation towards a new profile optimized to improve the operation of electricity systems [11]. According to the literature, various indices have been proposed to quantify the flexibility. For instance, the authors in [12] determine the energy shifting potential based on the index that reflects the additional energy use for a target change in power consumption for each hour of the day. For a combined heat and power system with thermal energy storage, the amount of flexibility is quantified based on the number of hours the energy demand can be delayed or forced [13]. In [14], the demand response (DR) control technology of residential heat pump is a market-based multi-agent control system and a priority, which can be regarded as a 'virtual price' that represents the willingness of the device to consume or produce the target power, is employed as the index to quantify the flexibility. Beyond the flexibility of heating systems, demand response flexibility and flexibility potential of a wider range of residential smart appliances (e.g., dishwashers, EV and domestic hot water buffers) is quantified in [15] by calculating the potential for realizing a certain increase or decrease of power within the comfort requirements of the customer as well as its time duration. In addition, cost curves of the energy shift are considered in [16] to quantify the amount of flexibility of buildings. Recently, a data-driven approach was developed in [17] to investigate the energy flexibility potential of building clusters by using survey data and available statics in Denmark for the worst case scenarios. The authors in [18] present a comprehensive overview of flexibility quantification approaches in power systems. Overall, for different technologies with various applications, there is a need to identify and employ different energy flexibility indicators such as the total demand decrease or increase, the duration of energy demand change, response time and the maximum power change in demand [19].

Although the above flexibility quantification methods have been proposed for HHPs, it is still imperative to develop a novel methodological framework for data analysis of SHHPs to extract the key information (e.g., demand diversity) for future network planning and to quantity the value of SHHPs for future electricity systems. In this paper, a comprehensive data analysis is carried out to understand the benefits of smart control of HHPs based on the real measurements collected from the field trial of the FREEDOM project. Key focus areas of the analysis considered in this paper include: i) flexibility analysis;

ii) heat pump demand diversity analysis; and iii) COP analysis. To summarize, the main contributions of this paper can be concluded as follow: :

- Develop a novel data-driven flexibility quantification framework for SHHPs by exploiting various types of real data collected from the first sizable trial of fully-optimized hybrid heat pumps in the world.
- Investigate and quantify the benefits of the improved Coefficient of Performance (COP) values obtained by using the smart control technology of HHPs. Additionally, the system value of smart control of HHPs is quantified through the whole-system assessment.
- For distribution network design, heat pump demand diversity analysis is carried out for SHHPs to estimate the coincidence factor across different numbers of customers.

The rest of this paper is organized as follows. Section 2 presents the proposed data-driven flexibility quantification framework for SHHPs. Section 3 illustrates the diversify of hybrid heat pump electricity demand. Section 4 introduces case studies showing the demand flexibility of different customers with time-varying price signals, the quantified SHHP electricity demand diversity and the benefits of the improved COP obtained via the smart control technology. Conclusions are given in Section 5.

2. Data-driven flexibility quantification of smart hybrid heat pumps

2.1. Smart control of hybrid heat pump

In the Freedom field trial [8], smart control developed for HHPs is based on Predictive Demand Control (PDC) technology that aims to optimize the performance of the heating system over the upcoming day and minimize energy consumption and energy cost while satisfying the comfort requirements of the customer. Traditionally, hybrid heating systems are controlled either on a time-switch, which may lead to an inefficiently high temperature of heating water, or on a constant weather-compensated heating water temperature, which results in redundant heat loss during the midnight [20].

Nevertheless, smartly hybrid heating systems can effectively address these issues by using PDC to gently run the HP and use a dynamically controlled flow temperature to gradually ramp up the HP overnight. The smart control technology can learn the thermal characteristics of the property and then construct a specific model for this property and heat system. Additionally, PDC provides the benefits of enhancing demand flexibility and reducing the total bill for customers by self-diagnosing cost-efficient demand reduction measures that could be applied to the home to increase fabric storage. Compared to conventional control systems, which switch between electricity and gas purely based on external temperature, the proposed dynamic control approach makes it possible to affect the COP by controlling the heating water temperature in addition to the impact of external temperature.

Beyond that, predictive control enables considerable functionality of HHPs for demand-side management and time varying energy prices by employing the property with SHHP as energy storage based on building thermal inertia. In particular, the strategy to shift demand is determined automatically by the smart control technology to balance the customer comfort requirements, the energy losses and the heat stored in the fabric of the property. More details on the smart control technology can be found in the references [8, 9] and the patents [21, 22].

2.2. Proposed data-driven flexibility quantification framework

As one of the primary benefits contributed by the smart control technology of HHPs, the flexible heating, quantified by preheating that involves heating the households earlier than it would be otherwise done while utilizing inherent heat storage in the fabric of the houses, would significantly enhance the capability of the system to integrate and utilize low-carbon generation, reduce the integration requirement of low-carbon generation and the firm generating capacity needed for maintaining the system security and avoid distribution network reinforcement. To this end, it is imperative to develop a novel preheating quantification framework for SHHPs that can estimate the capability of heat pump demand shifting based on various types of real measurements. Figure 1 presents the proposed data-driven flexibility quantification framework to estimate the preheating for each individual household.

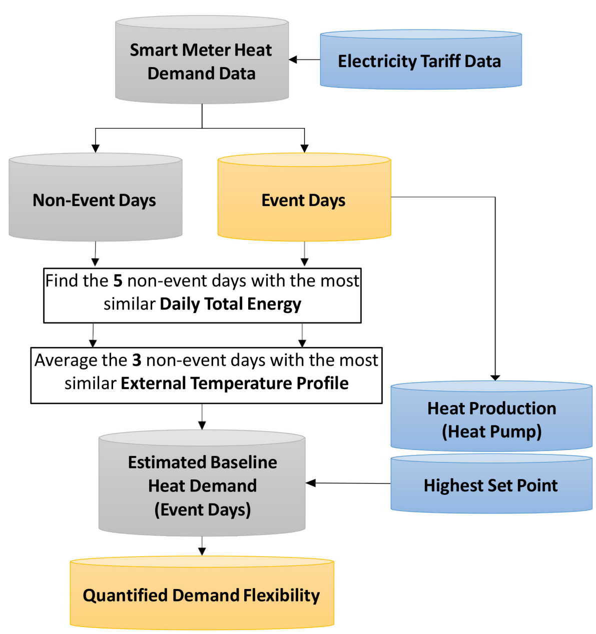

Figure 1: The proposed data-driven flexibility quantification framework for a single household.

Given the examined customer i and the total number of measurements during the trial period T, the required data measurements for flexibility quantification consist of the electricity tariff data $\Pi_i \in \mathbb{R}^T$, external temperature $E_i \in \mathbb{R}^T$, highest room temperature set point requested by the customer $S_i \in \mathbb{R}^T$, HP heat production (no request for gas boiler) $P_i^E \in \mathbb{R}^T$, gas boiler heat production $P_i^G \in \mathbb{R}^T$ and heat demand $D_i = P_i^E + P_i^G \in \mathbb{R}^T$. As illustrated in Figure 1, the first step is to split the above-mentioned datasets into "non-event days" and "event days", which refer to the set of days with and without time-varying price signals, respectively. Note that event and non-event days are trail terminology and refer to conducted trials which are planned. Let Ω denote the set of all days, $\Omega_E \in \Omega$ and $\Omega_N \in \Omega$ represent the set of event days and non-event days.

A necessary prerequisite for quantifying the capability of heat pump demand to be flexibly shifted is to establish the relevant baseline profiles, i.e. to determine the energy use patterns when flexibility is not requested (either through varying prices or direct instructions). Establishing baseline profiles for each customer needs to ensure that the estimated baseline heat demand of the tested event day exhibits similar daily energy demand requirements and external temperature patterns compared to the measured data. By eliminating the variations in these key drivers for heat demand patterns, the baseline estimation process aims to isolate the effect of interventions. To this end, for each of the event days $d_e \in \Omega_E$, daily total energy is calculated by $D_{i,d_e}^{total} = \sum D_{i,d_e}$. Furthermore, daily total energy for the non-event days can also be obtained by $D_{i,d_n}^{total} = \sum D_{i,d_n}$ where $d_n \in \Omega_N$. Based on the calculated daily total energy, the next step is to identify five non-event days with the most similar daily total energy for the event day d_e, as follows:

$$\Omega_{i,d_e}^{5*} = \arg\min_{\Omega_{i,d_e}^5} \sum_{d_n \in \Omega^5} |D_{i,d_n}^{total} - D_{i,d_e}^{total}| \tag{1}$$

where $\Omega_{i,e}^5$ represents the set of all combinations of 5 non-event days for customer i event day d_e and $\Omega_{i,e}^{5*}$ is the optimal set that contains the non-event days with the 5 most similar daily total energy.

Beyond the daily total energy consumption, external temperature, which fundamentally drives baseline heat demand, is considered as another criteria to identify the similar days. In particular, an optimal set of three non-event days $\Omega_{i,e}^{3*}$ is selected from $\Omega_{i,e}^{5*}$ to minimize the sum of distance between E_{i,d_e} the external temperature profile of customer i event day d_e and those of the three non-event days $\{E_{i,d_n}\}_{d_n \in \Omega_{i,e}^3}$. Finally, the estimated baseline demand can be obtained by averaging the the heat demand profile of the three non-event days in $\Omega_{i,e}^{3*}$ as follows:

$$\hat{D}_{i,d_e} = \frac{1}{3} \sum_{d_n \in \Omega_{i,d_e}^{3*}} D_{i,d_n} \tag{2}$$

Note that five and three days in the above steps have been selected based on the total number of days and a performance estimation test. After estimating the baseline demand, the flexibility of SHHPs is quantified by calculating the heat pump demand shift using the heat pump heat production data P^E_{i,d_e}. It is notable that the preheating period of day d_e is identified based on customer i's highest room temperature set point S_{i,d_e} to render preheating intervals only containing the low-price time steps that have lower temperature set points than the largest set point value of day d_e. Mathematically, the quantified flexibility of customer i day d_e at time step t can be calculated as:

$$\hat{F}_{i,d_e,t} = \begin{cases} P^E_{i,d_e,t} - \hat{D}_{i,d_e,t} & \text{if } S_{i,d_e,t} < max(S_{i,d_e}) \\ 0 & \text{otherwise} \end{cases}$$

It is notable that the baseline estimation method considered in the quantification framework can also be replaced by other baseline estimation approaches such as regression-based method [23] and the CONTROL group [24], which will be investigated in our future work.

3. Diversity of hybrid heat pump electricity demand

The concept of demand diversity is critically important for planning and analyzing electricity distribution networks. It is based on the fact that the timing of peak electricity use among a group of customers will not coincide exactly, so that the aggregate instantaneous peak demand of the group will be less than the sum of individual customer peaks. This is particularly important for planning the capacity of network components, which are designed to satisfy aggregate (i.e. diversified) peak demand (plus a certain margin) for a group of customers rather than the sum of individual peaks that are extremely unlikely to occur simultaneously.

Diversity is typically quantified using the coincidence factor, which is defined as the ratio between diversified and non-diversified peak per customer [25]. Given a dataset containing demand measurements for N customers, the coincidence factor j across an arbitrary number of customers can be calculated as:

$$j_n = \frac{D_C^{n\,max}}{\sum_{i=1}^{n} D_i^{n max}} \tag{3}$$

where n is the number of examined customers, D_i^{nmax} is the individual maximum demand of customer i and $D_C^{n\,max}$ represents the coincident peak demand of the n customers. Note that coincidence factors are essentially ratios of demand and thus are scalar metrics. Formula (3) relates to a specific grouping of n customers. It is important to highlight that in the case that $1 < n < N$, there exists $n!/n!(N-n)!$ possible customer combinations; this number grows extremely fast due to combinatorics.

Given that evaluating (3) across all combinations is computationally intractable, the use of appropriate sampling techniques such as bootstrapping is needed to approximate the value of interest. Since the sum of the individual peaks is always larger or equal to the coincident peak, the calculated coincidence factor always varies between 0 and 1. By definition $j_1 = 1$. In general, a lower value of j can be achieved when more customers are connected to the specific part of the distribution network analysed. Another aspect that is also imperative to highlight and applies to all three diversification metrics presented here is the fact that they converge to a steady-state value given a large number of consumers. This steady-state value can be denoted by the infinity superscript, as in j_{∞}. To deal with the computational issue, in practice, the following expression is typically used in network design to establish the diversified peak demand for a given number of customers [26]:

$$j_n = j_{\infty} + \frac{1 - j_{\infty}}{\sqrt{n}} \tag{4}$$

where j_{∞} is the coincidence factor for n customers and parameter j_{∞} is the coincidence factor for a very large number of customers (reflecting a fully diversified peak demand). The diversified peak demand is then calculated as:

$$D_n^{max} = j_n \cdot n \cdot D_1^{max} \tag{5}$$

where D_1^{max} is the peak demand of a single customer. The relationship between the coincidence factor and the number of customers for different values of fully diversified coincidence factor j_{∞} is shown in Figure 2. Note that the horizontal axis has a logarithmic scale. The figure shows that the coincidence factor decreases with the increasing number of considered customers for different values of j_{∞}, so that coincident peak demand for a large number of customers is less sensitive to the attributes of individual customers due to the effect of demand diversification. For a very large number of customers (beyond 10,000) the coincidence factors are very close to the fully diversified values, whereas when observing tens or hundreds of customers, their coincidence factors can still be significantly above the fully diversified levels. Detailed analysis of the coincidence factor for heat pump electricity demand is given in the Section 4.3.

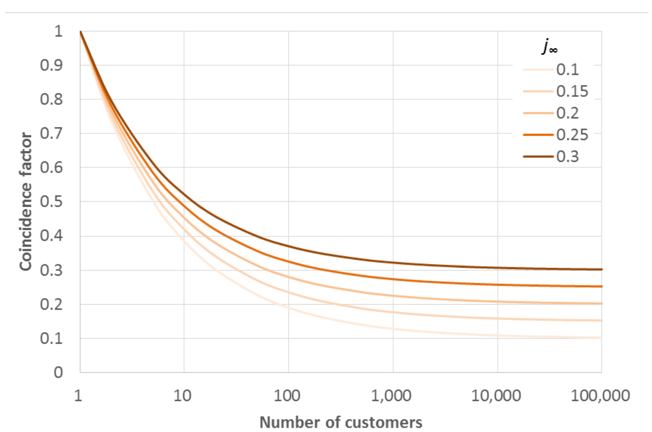

Figure 2: Coincidence factor as function of the number of customers.

4. Case Study and Results Analysis

4.1. Field trial data

The Flexible Residential Energy Efficiency Demand Optimization and Management (FREEDOM) project [8] was the first real-world trial in the world to include fully optimized control of hybrid heat pumps with predictive demand-side management and proactive consumer engagement. The field trial period ran from 1 October 2017 to 30 April 2018, and involved 75 households with hybrid heating systems deployed. Small sizes of heat pumps were deliberately chosen (8 kW and 5kW thermal rating for different brands) in order to capture situations when the heat pump is insufficient to heat the house and the system needs to switch to the gas boiler, but also to demonstrate the efficiency of the hybrid system with low heat pump investment cost.

Hybrid heat pump systems in participating homes were controlled using PassivSystems' advanced control that minimizes the total heating cost for a customer while respecting the customer's temperature settings, considering the cost of electricity and gas, outdoor temperatures and a variety of other parameters. All trial participants were provided with the PassivLiving smart-phone APP which enabled them to set their desired temperatures during the day (either by scheduling them in advance or by adjusting them in real time). Key measurements during the trial included: 1) low resolution gas and electricity consumption for the entire household; 2) high resolution electricity consumption and heat production of the heat pump; 3) pipe temperature sensors to measure heat delivery temperature; 4) room temperature sensors. The original measurement data were recorded at different time resolutions. For the purpose of the analysis presented in this paper all measurements were processed by PassivSystems and the observed parameter values reported as averages within half-hourly intervals. After the data cleaning process, 60 customers are considered in the case study.

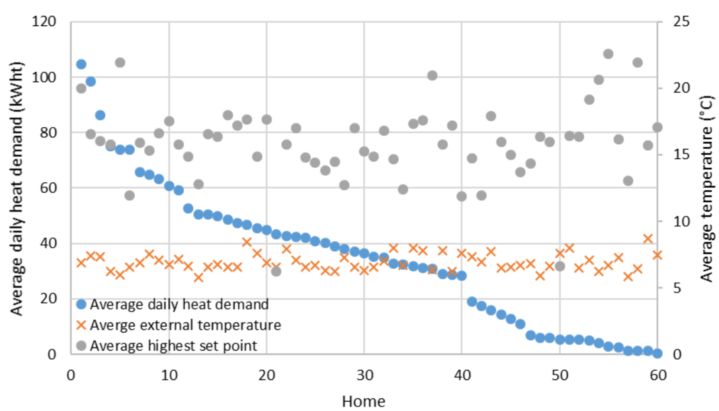

Figure 3: Key trial parameters per home.

4.2. Flexibility analysis

As mentioned earlier, heat pumps installed as part of hybrid systems had relatively low thermal ratings given that very high but infrequent heat demand during very cold periods could be supplied by gas boilers, which have significantly lower investment cost. Also, PassivSystems' control scheme ensured that the hybrid system always operated at the lowest cost for the customer, which as a consequence made heat pumps a less attractive heat supply option during cold conditions when only relatively low COP values were achievable. As a result, except for a negligibly small number of outliers, no heat pump during the trial was observed to produce more than about 5.8 kW of thermal output.

Figure 3 presents the average values of key trial parameters per customer: average daily heat demand, average external temperature and average highest set point, shown for all homes with usable data in the order of descending average daily heat demand. The figure shows that despite similar external temperatures and indoor temperature set points heat demand can vary significantly across different households. There are a number of possible reasons, including different insulation levels, occupancy patterns etc., however it appears that some datasets may have accuracy issues even after removing obviously bad data. For in-stance there are two homes (#21 and #50) with very low average set points at around 7 °C, but with heat demand comparable to other homes.

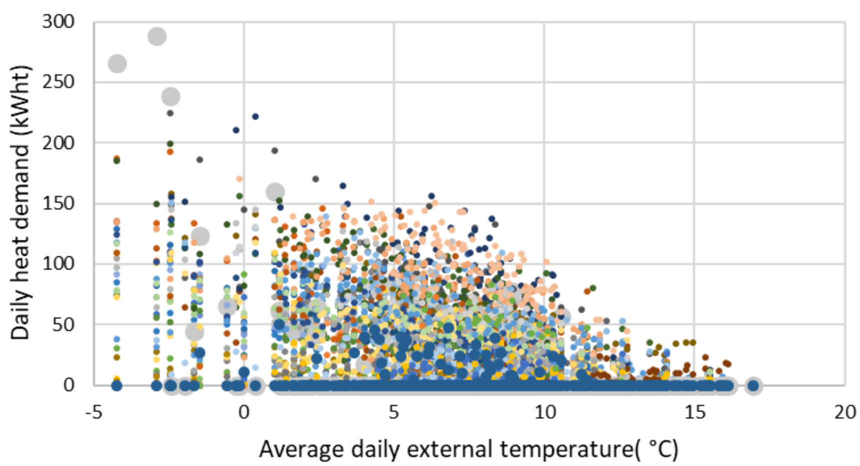

Figure 4: Scatter plot of daily heat demand vs. average external temperature (each home in different color).

Figure 4 presents the scatter plot of daily heat demand versus average daily external temperature, shown for each participating household in a different color. As expected, there is a clear trend of increasing heat demand with lower outdoor temperatures, although one can still detect outliers (e.g. points with zero heat demand at below-zero temperatures).

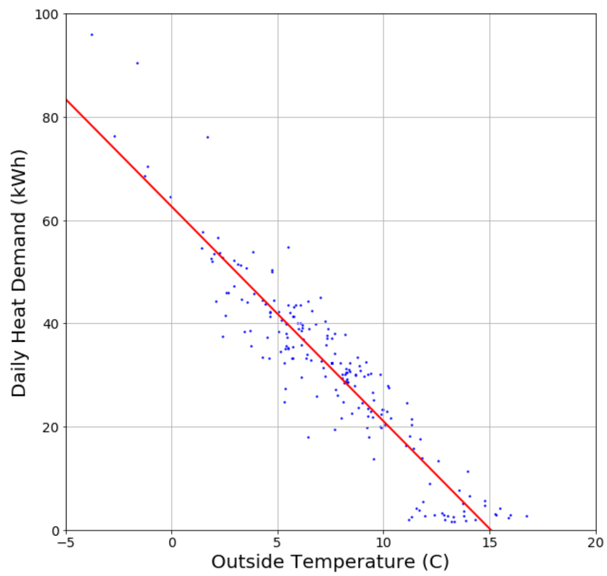

Figure 5: Scatter plot of half-hourly values for external temperature (ExtTemp) and COP for all heat pump providers.

The flexibility analysis is primarily based on heat demand data for the participants in the field trial. Total heat demand data for a household were assessed based on measurements of heat pump output and estimated heat output from gas boiler. A full dataset would entail about 9,600 data half-hourly points over the course of the trial (i.e. 48 points across 200 days). Daily heat demand per customer will obviously be negatively correlated with the out-door temperature, as illustrated in Figure 5.

4.2.1. Interventions with Economy 7 tariff

Economy 7 (E7) tariff experiments carried out in the trial assumed the electricity price from 00:30 to 07:30 was at the level of 70% of base (flat) electricity price, while at other times it was at 107% of the base price.

Figure 6 presents the heat demand and supply profile for one customer on Economy 7 tariff for 30 November 2017. The average external temperature during this day is 3.2 °C. For the first y-axis (left), the blue line and the orange line represent the actual and the estimated baseline total heat production, respectively. In addition, the blue and red shaded areas represent the heat output from the heat pump and the boiler, respectively. For the second y-axis (right), the red dashed line indicates maximum measured radiator flow temperatures. The output of heat pump on E7 tariff changes to capture the opportunity to use less expensive electricity overnight. The heat pump produces heat at a relatively low output level (around 1 kW) and with relatively low radiator temperatures (around 30 °C) in order to maximize the COP while preheating the home in

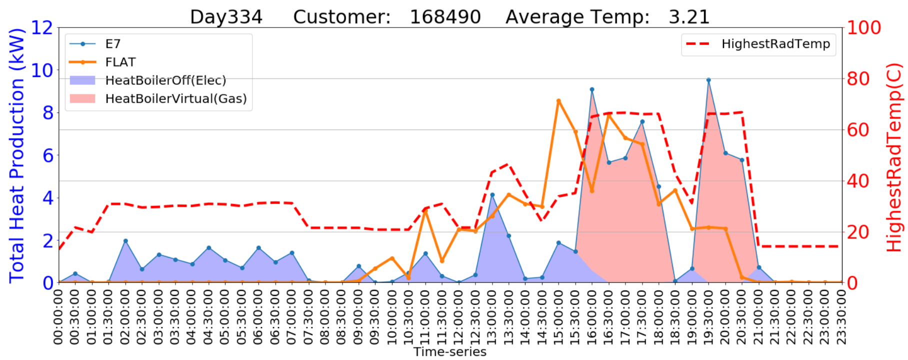

Figure 6: Daily heat demand and supply profiles for customer 168490 with Economy 7 tariff on 30 November 2017.

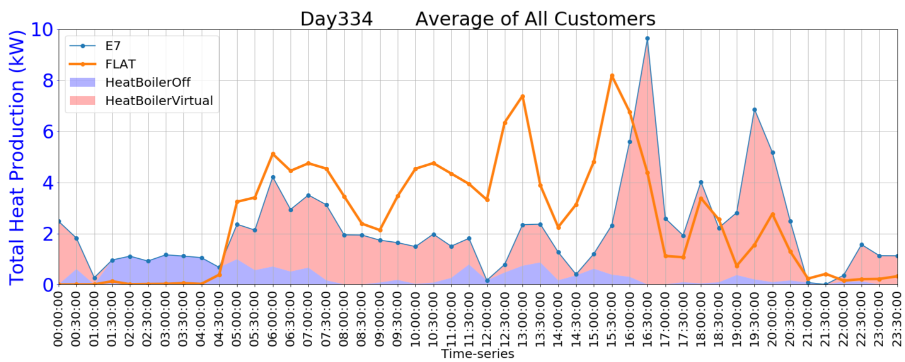

Figure 7: Average daily heat demand and supply profiles for all customers on Economy 7 tariff on 30 November 2017.

order to help to meet the temperature set points during the day.

The averaged heat demand and supply profiles across all E7 customers are shown in Figure 7 for the same date (30 November 2017). Similar as before, the heat pumps operate more during the less expensive night tariff, although at relatively low output to maximize efficiency, allowing that less heat is being provided during the day. To further illustrate the effect of E7 tariff on the use of heat pumps to supply heat, Figure 8 and Figure 9 show the heat supply and demand patterns for two customers during the period 27-30 November 2017. The heat pumps are again predominantly operating during the night, pre-heating homes to take advantage of the low electricity tariff. Heat pumps are only used during the day when relatively low temperature set points need to be maintained. In all other cases, and in particular when set points reach 20 °C, gas boilers are switched on to supply heat.

Heat pump operation during E7 periods is also driven by temperature set point schedules specified by the customers. This is illustrated in Figure 10 for

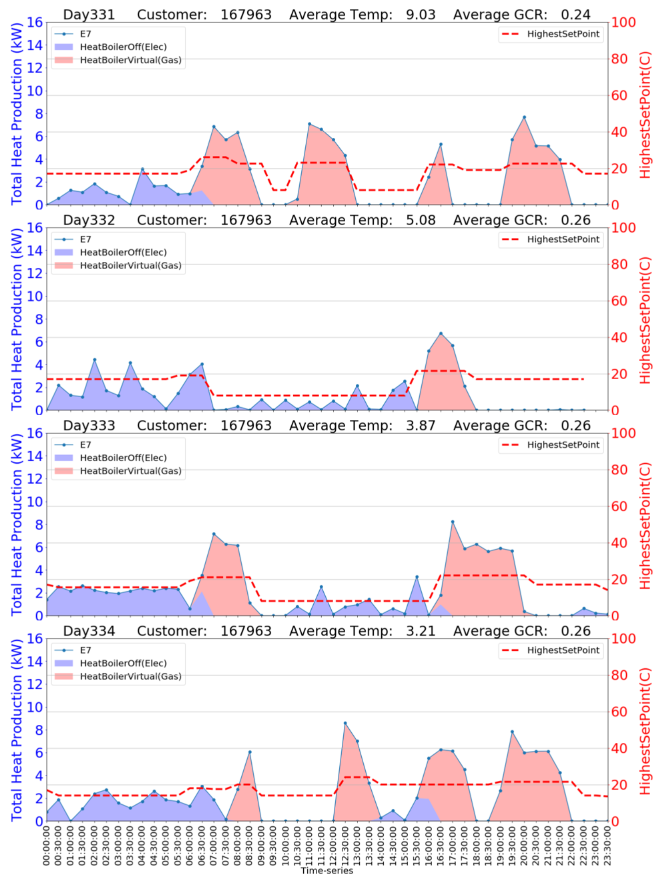

Figure 8: Daily heat demand and supply profiles for customer 167963 with Economy 7 tariff for period 27-30 November 2017.

two E7 customers over the period 27-30 November 2017. The first customer has a higher overnight temperature setting (17 °C) than the second one (12 °C), while at the same time the maximum temperature setting during the day was around 22 °C for the first customer and about 26-27 °C (and occasionally up to 30 °C) for the second. Both customers had daytime setback temperatures set to 8 °C. Higher variability of temperature set points for the second customer resulted in lower usage of heat pump during the night, given that the night-time set points were low, and daily set points high, requiring the use of high heat output from gas boilers.

4.2.2. Interventions with Economy 10 tariff

Economy 10 tariff experiments in the FREEDOM trial were set up by assuming a lower electricity price (70% of base price) during the following periods in the duration of 10 hours: 00:00 to 05:00, 13:00 to 16:00 and 20:00 to 22:00.

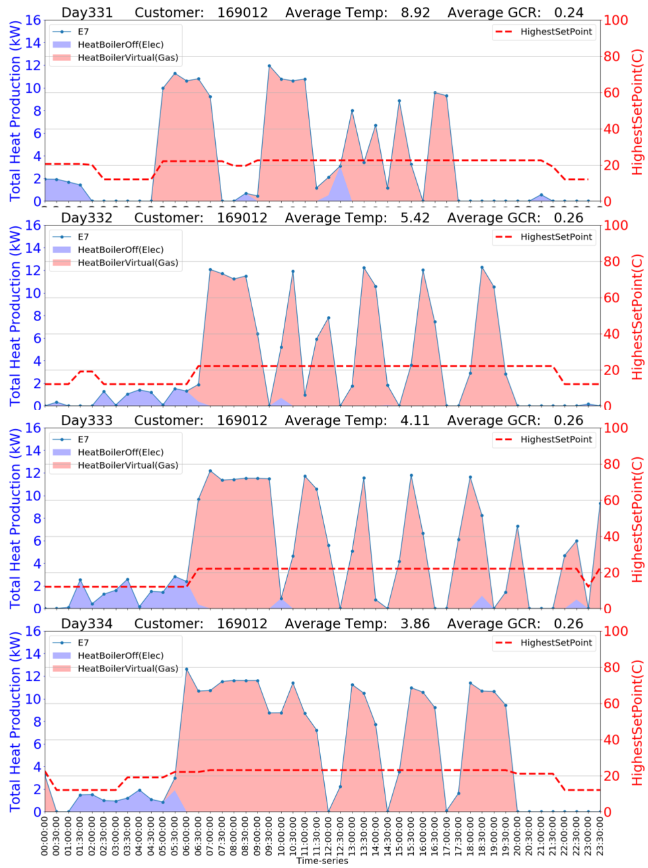

Figure 9: Daily heat demand and supply profiles for customer 169012 with Economy 7 tariff for period 27-30 November 2017.

At all other times the electricity price was 107% of the base price. Figure 11 shows the half-hourly heat demand and supply profiles for a single customer in the trial (No. 166491) on Economy 10 tariff, on 3 December 2017. The average external temperature during this day was 8.2°C. The chart also shows the highest observed radiator temperature in each half-hourly interval. As with the E7 results, the heat supply profiles of E10 customers are compared to the baseline profiles when a flat electricity tariff is applied.

The trial results show very clearly that the hybrid heat pump system responds to the three lower tariff periods by increasing the heat pump use in these periods compared to the baseline profile. Outside of these windows gas boilers are used to meet the heat requirements. Given the relatively high outdoor temperatures, the required radiator temperatures can be maintained through heat pumps most of the time, and the boiler is only used during a few early morning hours.

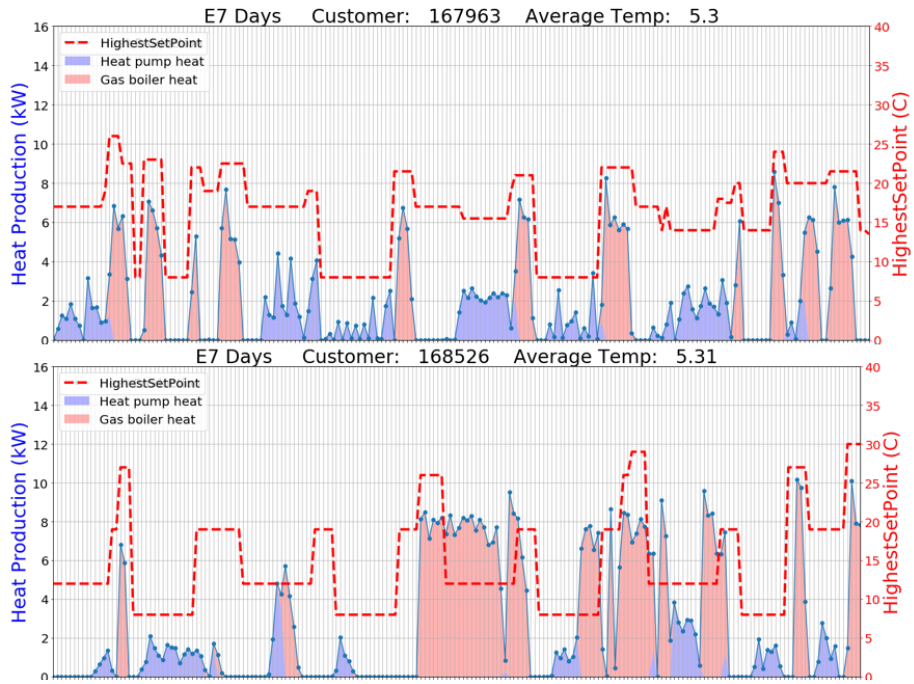

Figure 10: Heat demand and supply profiles for customers 167963 and 168526 with Economy 7 tariff for period 27-30 November 2017.

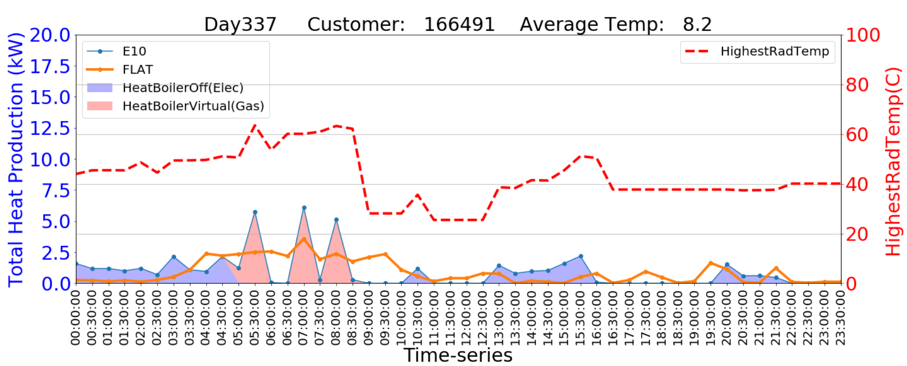

Figure 11: Daily heat demand and supply profiles for customer 166491 with Economy 10 tariff on 3 December 2017.

The heat supply profiles for the same customer for the following day (4 December 2017) are shown in Figure 12. The average external temperature for this day is similar as on the day before (around 8°C), but the required radiator temperatures are higher in the afternoon, triggering a higher usage of the gas boiler and consequently lower use of heat pumps in the after-noon and evening

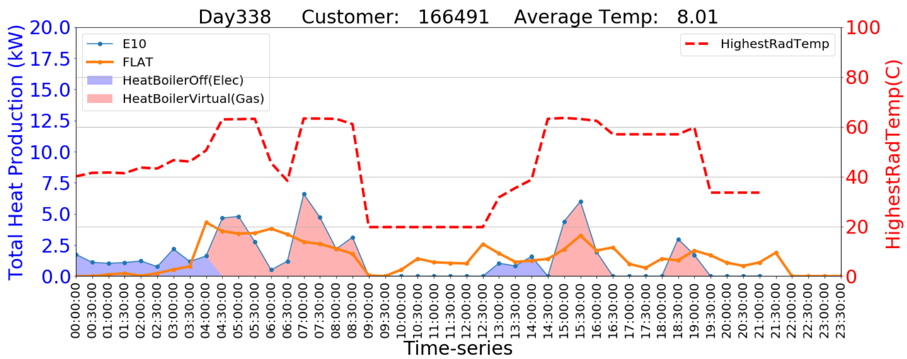

Figure 12: Daily heat demand and supply profiles for customer 166491 with Economy 10 tariff on 4 December 2017.

low tariff windows.

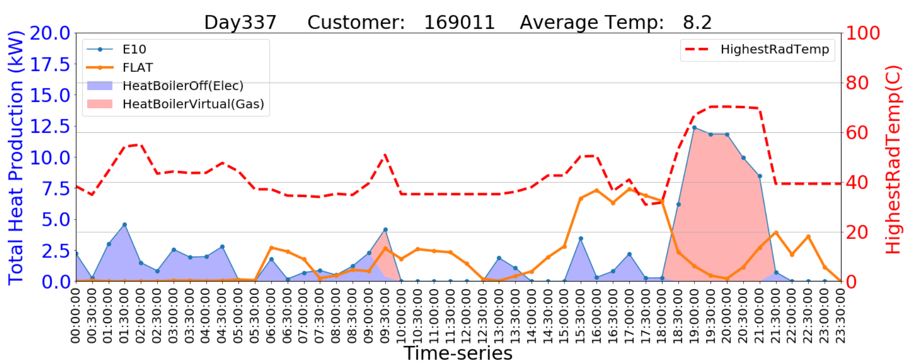

Figure 13: Daily heat demand and supply profiles for customer 169011 with Economy 10 tariff on 3 December 2017.

The same daily heat supply time series are plotted for another customer (No. 169011) in Figure 13 and Figure 14. In this example there heat is still produced by heat pumps during the night, where there was virtually no heat supply with a flat tariff. In the other two E10 windows, however, there is less pronounced heat pump usage as the higher temperature set points and higher requires radiator temperatures trigger the use of gas boiler.

The average heat supply profiles across all E10 customers for 3 and 4 December 2017 are shown in Figure 15 and Figure 16, along with comparable heat profiles under a flat tariff. The average heat pump usage increases during the night on both days, while on the first day there is also visible contribution from heat pumps during afternoon and evening E10 windows. On the second day the use of heat pumps during the day is significantly lower despite a similar outdoor temperature, as the result of differences in required temperature set points as well as occupancy patterns (3 December was a Sunday and 4 December a

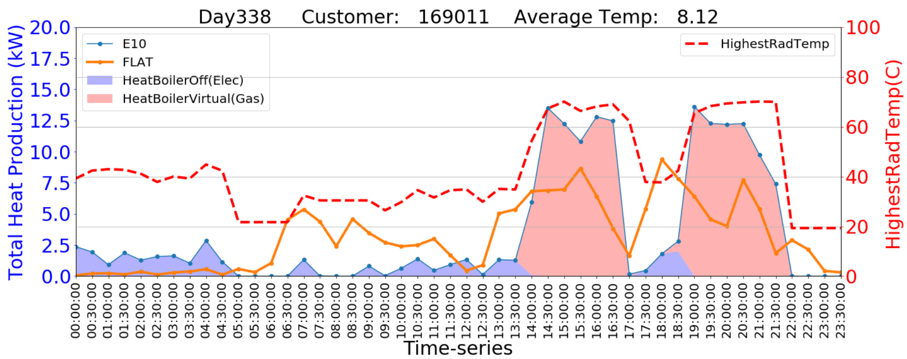

Figure 14: Daily heat demand and supply profiles for customer 169011 with Economy 10 tariff on 4 December 2017.

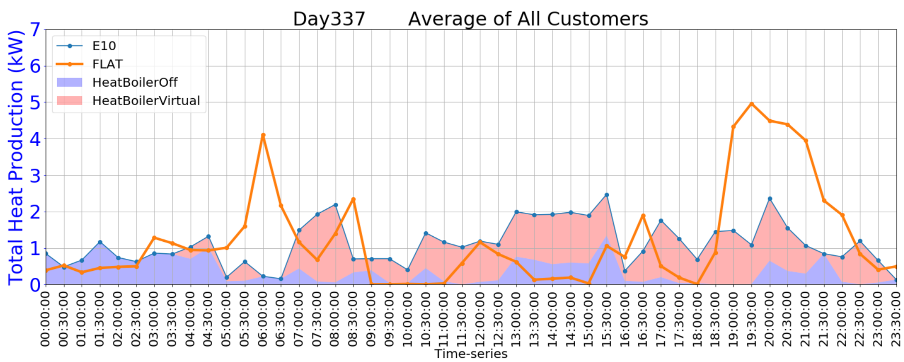

Figure 15: Average daily heat demand and supply profiles for all customers on Economy 10 tariff on 3 December 2017.

Monday).

Finally, to demonstrate the impact of outdoor temperature variations on the operation of hybrid heat pumps under Economy 10 tariff, Figure 17 shows how on a colder day (30 November) the heat requirements are covered by gas boiler at the level of 93% and only 7% from heat pumps, while with milder temperatures (3 December) the share of heat pump increases to 34%.

4.2.3. Quantifying hybrid heat pump flexibility

We use the flexibility parameter assumption on the trial data for E7 and E10 experiments by quantifying how much of the heat pump demand has been shifted compared to the baseline heat supply profiles based on flat electricity tariff. In Figure 18, the quantified volume of preheating across all customers is presented during low-price windows of E7 and E10 events, and expressed as average per customer along with 95% confidence intervals. Note that not all half-hourly intervals during low-price windows in E7 and E10 experiments are

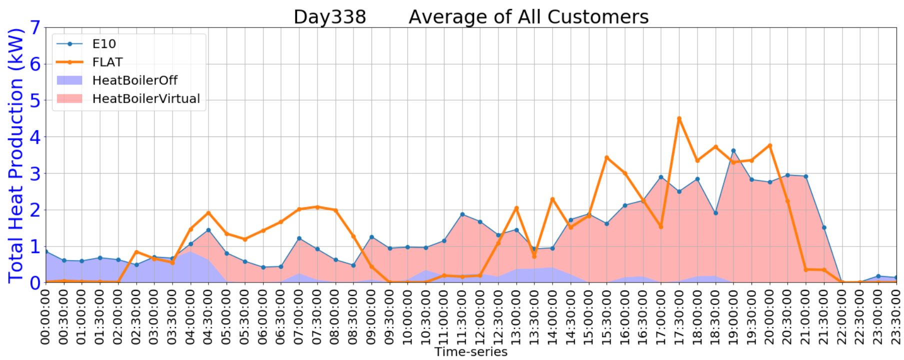

Figure 16: Average daily heat demand and supply profiles for all customers on Economy 10 tariff on 4 December 2017.

automatically classified as involving preheating. According to the customer's room temperature set point, the preheating periods for a given customer only consist of those half-hours of E7 and E10 events that have lower temperature set points than the highest set point value over a day. It can be seen that the SHHPs can successfully shift the demand to non-peak hours (e.g., midnight). In particular, higher preheating values before the end of events (e.g., 6:00am-7:00am, 15:00pm-15:30pm and 21:00pm-21:30pm) can be obtained than those of the beginning of events (e.g., 0:00am-5:30am, 13:00pm-14:30pm and 20:00pm-21:00pm). The volume of HP output shifted as the result of varying price experiments, compared to the baseline profile, can be further used as an input into the whole-system model [27] that minimizes the total operation and investment cost of the power system subject to security and carbon constraints to quantify the benefits of SHHPs, which will be investigated in our future work.

4.3. Analysis of SHHP electricity demand diversity

In order to inform the impact analysis of hybrid heat pumps on electricity distribution networks, the coincidence factor of heat pump electricity demand is quantified from the field trial data. The following approach was adopted:

- To establish the contribution of hybrid heat pumps to baseline peak demand, which occurs during the winter, a subset of half-hourly electricity demand data is considered that included days with at least one negative external temperature measurement.
- To maximize the size of the customer sample for coincidence factor calculation we included all days in which at least 41 half-hourly data points (out of 48) existed for heat pump electricity demand.
- This approach resulted in 34 customers over 11 days being included in the calculation (out of the 23 days in total that had at least one negative external temperature measurement).

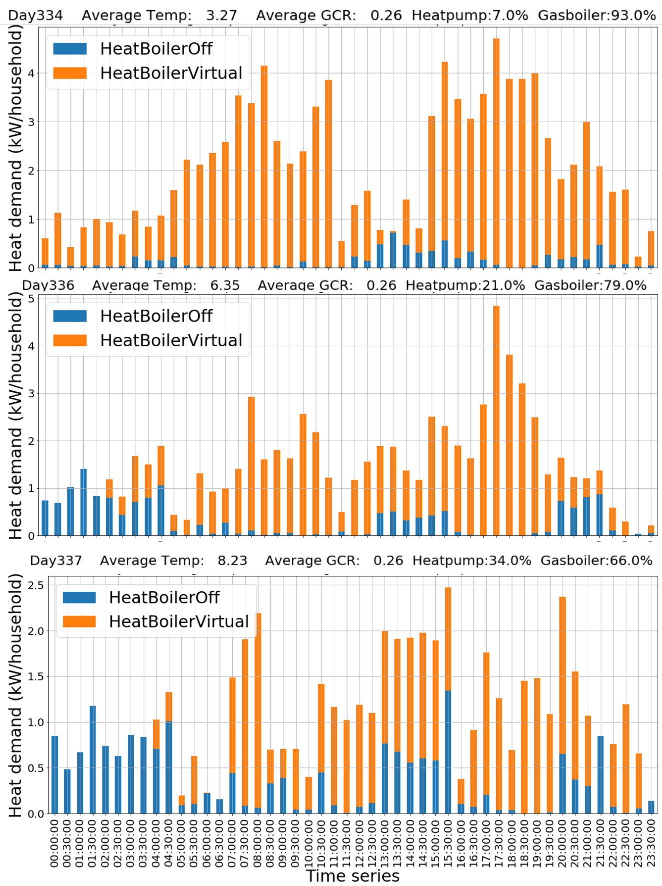

Figure 17: Average daily heat supply split between heat pumps and boilers for Economy 10 customers on 30 November, and 2 and 3 December 2017.

The coincidence factor of 0.27 was found for the entire subset of 34 customers. In addition to the full subset, the coincidence factors were also quantified for customer sample sizes between 2 and 33, as shown in Figure 4.10. These samples were drawn between the 34 customers randomly 100 times and their average coincidence factors are included in the chart. The coincidence factor follows a fairly monotonous decreasing characteristic with only slight variations.

For the purpose of using the findings on the diversity of heat pump demand in the distribution network analysis, the calculated coincidence factor curve is approximated with an empirical curve following the expression used to plot Figure 19, with the parameter j_∞ equal to 0.12. It can be seen from Figure 2 that this parameter choice provides a good fit for larger customer group sizes, which are also of most interest for network impact calculations, while for smaller group sizes it provides a slightly more conservative (i.e., higher) estimate of the coincidence factor.

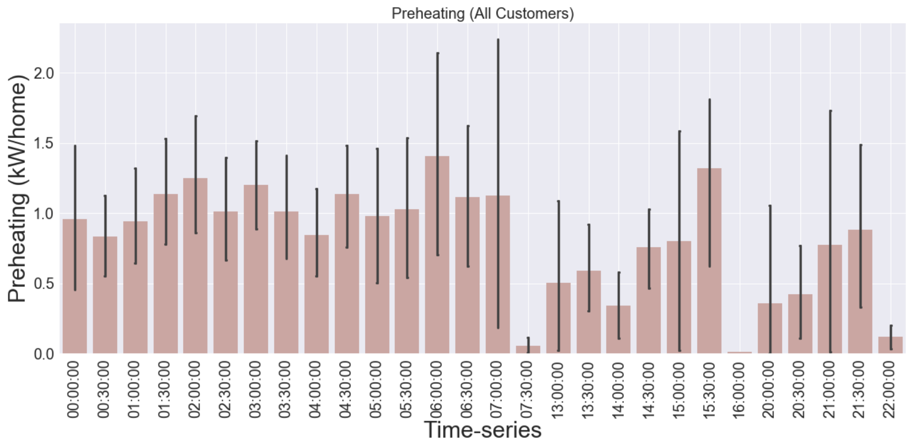

Figure 18: Preheating for all customers during E7 and E10 events.

4.4. Analysis of Coefficient of Performance (COP)

This section analyses the observed values for the COP based on trial measurements. COP is a key performance indicator for any heat pump system, quantified as the ratio of heat output from the heat pump and electricity input used by the heat pump. For air-source heat pumps in particular the COP varies considerably as function of external air temperature and is therefore important to characterize in order to adequately quantify the impact of heat pumps (whether hybrid or electric-only) on the wider electricity system.

Half-hourly values for COP have been derived from the measurements by dividing the heat output from heat pumps with their electricity consumption for those half-hourly intervals where a heat pump was operating. Given that the external temperature (or more precisely the temperature differential between external air and heat pump output flow) is the key parameter that drives the variations in COP, Figure 20 shows the scatter plot of COP and external temperatures for all half-hourly data points.

The scatter plot of half-hourly values presents a high degree of variation, with data points ranging from just above zero to over 8. This represents a much higher range of values than those typical for long-term COP variations, which can be explained by the way the data was collected. In half-hourly intervals where a heat pump only operated for a short time and/or at the low level, any inaccuracies in measurements as well as the consumption of the circulation pumps (included in total heat pump power consumption) may easily distort the COP and result in very high or very low values.

Therefore, to quantify the COP vs. external temperature characteristic to be used in power system modelling it is more appropriate to quantify daily average COP values based on daily values for heat pump thermal output and electricity input, which mostly avoids the issues arising with sampling heat pump operation in half-hourly intervals.

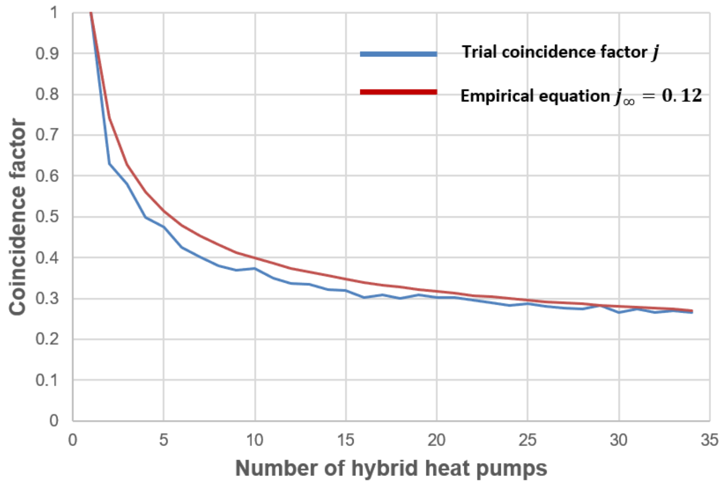

Figure 19: Coincidence factor for heat pump load as function of the number of customers.

Figure 21 shows the average daily COP values averaged across all participating households and plotted against average daily external temperatures. The level of variation is expectedly much smaller than for half-hourly values. According to the linear best fit, the average COP values are 2.6 for 0°C, 3.4 for 5°C and 4.0 for 10°C. These values are somewhat higher than typical COP values for electric-only heat pumps (such as e.g. those used by the UK government in [28]), at least in part because of the advanced operational strategies employed, such as running the heat pump overnight with a lower output temperature, therefore achieving a better COP.

Given that the smart control algorithm applied in the trial participants' hybrid heat pump systems optimizes the user's cost given the cost of electricity and gas, while taking into account the achievable COP of the heat pump, the COP can be expected to vary according to the Gas Cost Ratio (GCR) value applied for different periods and different customers. Figure 22 presents the observed daily average COP values against average GCR levels valid for the respective days. Although there is significant variation in COP for a given GCR level, there is a clear trend of higher COP values being recorded for lower GCR levels (i.e. when gas is relatively cheaper than electricity). This is expected given that with higher GCR it becomes economical to operate the HP at lower COP levels.

The smart control of HHPs demonstrated that the COP of HHPs can be improved. In order to understand the benefits of improved energy efficiency if the technology is rolled-out across the UK, a number of studies were carried out assuming that the COP of the HHPs system could be potentially improved by 5% and 10%. The studies were carried out for the 100 gCO_2/kWh carbon targets. In this context, we adopt the Whole-electricity System Investment Model

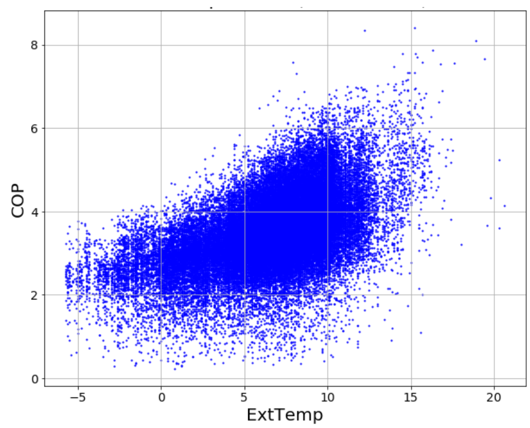

Figure 20: Scatter plot of half-hourly values for external temperature and COP for all customers.

(WeSIM), which simultaneously balances long-term investment decisions against short-term operation decisions, across generation, transmission and distribution systems, in an integrated fashion. Detailed information of the WeSIM model can be found in our previous work [29] [30] and [27]. The results of the studies are presented in Figure 23.

As shown in the results, the improved COP allows for a reduction in the power system operating cost, investment cost of electricity generation as well as network costs (primarily distribution network costs); the main savings however are in reduced opex and capex of low-carbon generation. In the 100 gCO_2/kWh cases, the benefits are between 1.8 - 2.4 £bn/year. This implies that the system value of improved COP enabled appropriate control of the HHPs may be significant to GB electricity systems.

Combining the smart control functionalities to maximize the benefits of "preheating" and improving COP enhances the system value of HHPs. In this context, the study with 100 gCO_2/kWh carbon target was carried out assuming smart control of HHPs that enables provision of balancing services while COP is assumed to be enhanced by 10%. In addition, the impact of having other flexibility sources (i.e. energy storage and DSR in non-heat demand sectors) was investigated. The difference between the costs of the system with and without smart control in a low and high flexible system is presented in Figure 24. Given the assumption of 100% HHP penetration, two levels of flexibility: (i) low and (ii) highly flexible HHPs cases correspond to 25% and 100% of households that take part in providing flexibility through smart control. In the UK, around 75% of households have access to gas, which would allow for a large-scale deployment of HHPs without additional requirements for the gas distribution infrastructure, while at the same time avoiding the overloading of the electricity grid. It can be concluded that: 1) SHHPs allow more low-carbon and zero-marginal-cost plants to be installed hence; it reduces the electricity opex while driving higher

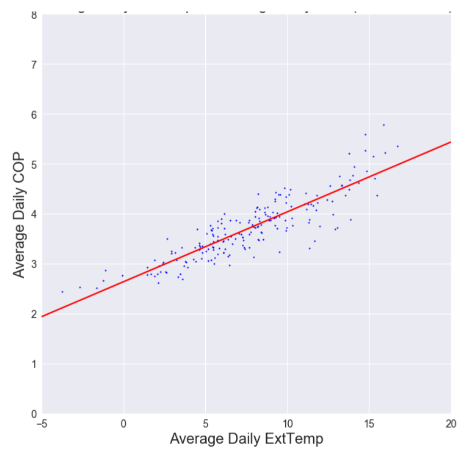

Figure 21: Scatter plot of daily average external temperature versus average daily COP.

investment in low-carbon generation. In addition, the smart control reduces the cost of distribution network reinforcements; 2) In the low-flexible system, the system value of the smart control is £5.3 bn/year. This saving is attributed to the smart control of HHPs that enables provision of flexibility and balancing services to the electricity system; 3) In the highly-flexible system, the value of smart control of HHPs reduces to £2.1 bn/year, given the competition from other flexibility sources that are present in the system.

5. Conclusions

To investigate and quantify the benefits of SHHPs, this paper presents a comprehensive analysis based on the fine-grained data collected from the world's first sizable trial of SHHPs, the FREEDOM trial. A novel data-driven flexibility quantification framework is proposed to quantify the capability of SHHPs to perform demand shifting and isolate the effect of interventions. Shifting of heat pump demand in time-varying price experiments was typically reflected in preheating of homes to take advantage of low overnight electricity prices. The volume of demand shifted through preheating is used as proxy to quantify the flexibility of shifting SHHP demand in time in response to price signals. Furthermore, diversity of SHHP demand is quantified as a critical input into electricity distribution impact assessment. The calculated coincidence factor curve determined from trial data was approximated with an empirical curve with the coincidence factor for a very large number of customers equal to 0.12. Finally, the observed values of the SHHP COP have been analyzed in order to estimate the relationship between the power consumption and the heat output of SHHPs. The observed average values of COP were 2.6 at 0°C and 4.0 at 10°C. These values are somewhat higher than the typical COP values found in the literature for electric-only heat pumps, as the result of the smart control solution deployed in the trial.

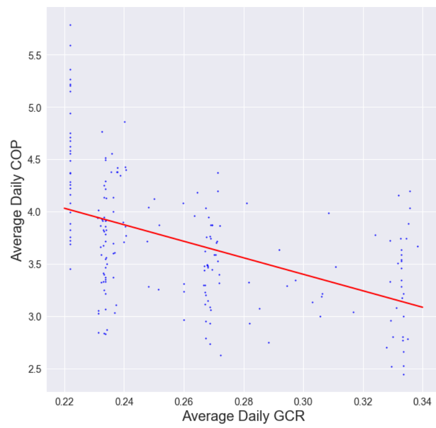

Figure 22: Average daily COP observations as function of average daily GCR value.

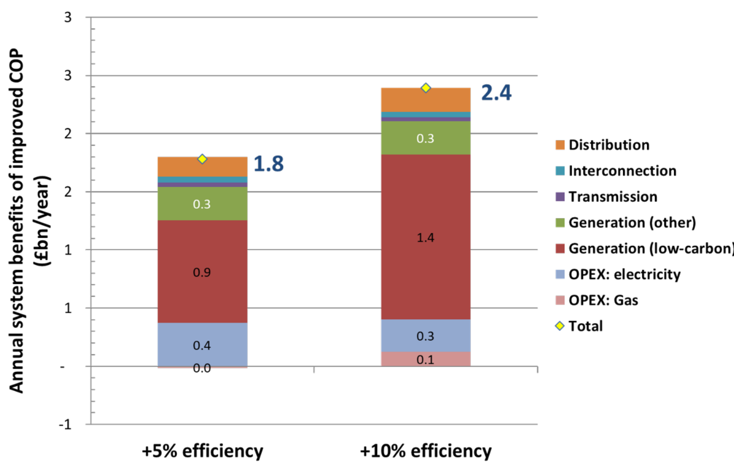

Figure 23: Benefits of improved COP attributed to smart control of HHPs.

Finally, the system value of the smart control of HHPs reflected in the improved COP is quantified using on a whole-system model. Assuming a COP increase of 5-10%, the value of smart HHP control is found to be between 1.8 and 2.4£bn/year in the 100 gCO_2/kWh case. Beyond that, the results demonstrate that smart HHP control would significantly enhance the capability of the system to integrate and utilize low-carbon generation, reduce the required volume of low-carbon generation and the volume of firm generating capacity needed for maintaining the system security, and reduce the need for distribution network reinforcement. The value of smart HHP control is found to increase if the COP can be improved. Assuming a 10% increase in COP can deliver whole-system benefits between 2.1 and 5.3£bn/year, depending on the system flexibility. With regards to the whole system study we could expand it on other

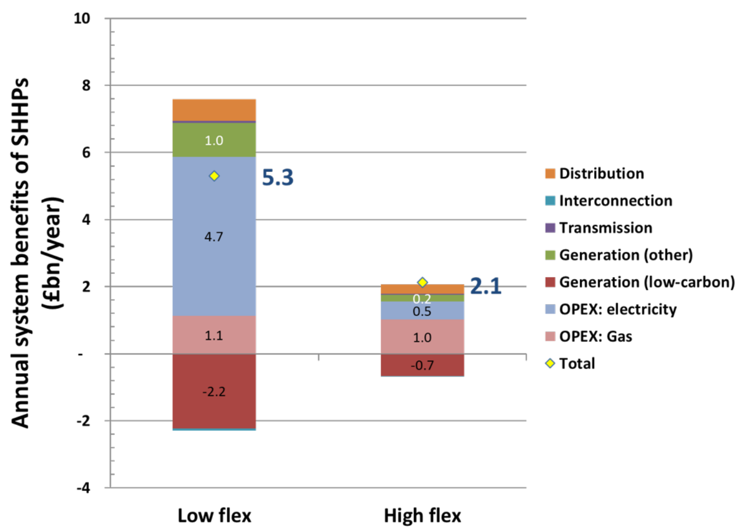

Figure 24: Benefits of smart control of HHPs.

countries where climate conditions must be taken into account.

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