Domestic demand-side response on district heating networks

This paper presents results from a field study that deployed demand shifting technology on a sample of 28 homes connected to a district heating (DH) network in England over the winter of 2015/2016. The aim was to improve the load factor of the participating households.

Improving load factors has the potential to improve the attractiveness of DH and accelerate the roll out of DH networks in the UK. Capital costs are lowered by reducing required boiler capacity and pipework sizes. Operational costs are reduced by increasing the coverage of the primary plant and reducing heat losses and pumping energy.

In addition to specific insights for the deployment of demand shifting on DH networks the results provide general lessons for the utilization of building thermal inertia for demand shifting.

The interventions tested have increased the load factor of the participating homes from 0.29 to 0.44. Achieving this has led to an increase in energy demand of approximately 3% however estimated network cost savings exceed this increased energy cost. While some participants noted the altered operation of their heating systems and expressed concern, the majority indicated they would be willing to participate in a commercial scheme for a small financial reward.

Keywords: demand-side response, district heating, control systems

Introduction

The use of information and communications technology (ICT) to improve the operation of electricity networks forming a ‘smart grid’, is a topic that has attracted academic and commercial attention in recent years. The deployment of distributed computing technology that has the ability to automatically shape energy demand and deliver network benefits has been addressed in multiple studies, see for example Agnetis et al’s (2011) report on the LINEAR project, Dolan et al’s (2012) report on the NINES project in Scotland or Boehm et al’s (2012) overview of the MIRABEL project. To date, however, large scale commercial deployments have focused on more rudimentary approaches.

Many of the techniques that have been discussed with reference to electro-thermal energy storage and demand shifting (Hawes, Feldman, & Banu, 1993) (Sweetnam, Spataru, & Barrett, 2014) are equally applicable to homes connected to DH networks. Similarly, while this paper focuses on DH, the technology deployed may also be applied for the control of electro-thermal devices and therefore the practical lessons of the field trial are broadly applicable.

This paper presents the results of a field study that deployed a prototype demand shifting technology on a sample of homes connected to an operational district heating (DH) network in the South West of England over the winter of 2015/2016. The technology, which has been developed by PassivSystems, a HEMS provider, consists of an internet-connected in-home hub and a cloud based demand coordination service. The hub has computing capacity and, in addition to providing a user interface, runs an optimising control algorithm that aims to deliver the households comfort requirements while minimizing energy use and respecting any demand constraints. The demand coordination service calculates a demand shaping signal for each of the participating homes in order to shape network level demand in a coordinated and, optionally, fair manner by equalising the impact of increased overnight temperatures for example.

The efficiency of delivering heat via a district heating network is influenced by the operational regimes of the heat supply plant, the amount of pumping energy used, and amount of energy lost in the network pipework. The peak heat demand is an important determinant of the capital cost of constructing the network. Shaping the heat demand and the reduction of demand peaks, therefore, has the potential to improve network efficiency and reduce capital costs, within the system boundary of the network.

The primary aim of the field trial was to gain an understanding of the impact of HEMS and the demand coordination service on the heat demand profiles of the participating households and the thermal comfort of the participants. A number of research questions arise from this aim; What is the impact of the intervention on the load factor of the homes in question? How are internal temperatures affected by any demand shifting? Do participants notice and how do they react?

This paper begins with a brief overview of studies on the efficiency of heat networks and work on heat demand shifting that has been carried out mainly in connection with electrically driven heat pumps. The experimental design and data gathering and analytical methodologies are then discussed before the results of the project are presented and some concluding remarks are provided.

Demand Response & District Heating Networks

Over the last number of years, a significant amount of research effort has been invested in the area of demand response and smart grids. From high-level modelling studies to pilot implementations of co-ordinated control approaches. The potential for flexible demand in the domestic sector to contribute operation and capital cost reductions to electric networks has been widely documented, see for example Kolokotsa (2016). A number of authors have focused on specific electrical loads within the house such as flexible usage of wet appliances such as dishwashers (Finn, O'Connell, & Fitzpatrick, 2012) or encouraging active shifting of demand by occupants (Torriti, 2012).

The potential to use building thermal inertia as a resource (Hawes, Feldman, & Banu, 1993), has also been discussed for many years. Thermal inertia is useful to the smart electricity grid where heating is provided using electricity either directly or via a heat pump and similar approaches apply to district heating networks. More recently Le Dréau and Heiselberg (2016) have compared the potential for demand shifting in a poorly insulated dwelling and a Passivhaus standard dwelling in a simulation study. They find the time constant[i] of the dwelling to be a crucial determinant of its ability to shift demand. The poorly insulated dwelling which has a time constant of 28h can absorb a relative large volume of energy but quickly falls below thermal comfort limits without heat input. The Passivhaus standard dwelling which has a time constant of 108h quickly overheats if used as an energy store however can remain within comfort limits for a long period without heat input. A number of authors, such as Laaouatni et al (2017) have investigated the potential for phase-change materials and other innovations to overcome these limitations.

In the UK both academics, such as Strbac et al (2012) and consultants such as Poyry (2010) and Sustainability First (Owen, Pooley, & Ward, 2012) among others, have carried out modelling studies and attempted to value the potential contribution of domestic sector flexibility to the smart grid. While the metrics used and the absolute conclusions vary, the overwhelming conclusion is that demand flexibility is beneficial for the operation of electricity networks.

A much smaller body of work has focused on demand flexibility on district heating networks although demand flexibility equally has potential to contribute to the operation of these networks. One of the early works to recognise this is by Van Der Meulen (1988) who pointed out that networks often have low operating cost (e.g. the use of free waste heat) and high capital costs and therefore delivering peak reductions can have a significant impact on network lifetime costs. The study describes a load control approach using the thermal inertia of the building and refers to a field trial however this is not described in detail. More recently Lund et al (2016), highlight the importance of flexibility in delivering 4th generation DH networks and Smart Energy Systems that optimise both demand profiles and network temperatures in a holistic approach. Further to this, Brand et al (2014) describe a simulation study of two way flows of heat energy on DH networks, an innovation that would certainly push the boundaries of DH network operation and drive the adoption of the type of intelligent demand control discussed in this paper.

The shape of the heat demand profile on DH networks is driven by the mix of consumers, their habits and the type of heat delivery technology installed in the connected consumer properties. In networks with predominantly domestic demand the space heating controls within the home and the method of hot water delivery are very important. To date, the vast majority of heat delivered in the UK domestic sector has been through individual gas boilers. Gas boilers are well suited to rapid heat provision and therefore dwellings in the UK commonly employ two short morning and evening heating periods (Huebner, et al., 2013) controlled by a timer and thermostat. DH networks in the UK inherit the ‘cultural norm’ of this approach to heating operation which may create more pronounced peak heating demand when compared to schemes in countries with a longer history of DH usage.

The impact of reducing peak heat demand or increasing the load factor has obvious impacts on the capital costs of networks which are sized to meet peak demand. Pipes, pumps and central plant can all be down-sized. Where an existing network is under consideration, reduced peak demand in the existing homes can facilitate network expansion without additional primary infrastructure.

In terms of operational costs, where the main plant is a combined heat and power (CHP) unit as is common on UK networks, higher load factors produce benefits through reduced usage of expensive and often more carbon intensive auxiliary boilers and therefore more intensive use of the main plant. Where alternative heat sources, such as heat pumps (which may be exposed to variable electricity tariffs) are used the optimum demand profile becomes more complex however is equally achievable using the approach described here. Lower peak flow rates mean reduced pumping energy demand and, if network flow temperatures are also reduced in line with demand, reduced pipework heat loss can also be delivered.

In addition to the early work of Van Der Meulen, a number of other authors have described approaches to aggregated control some of which have been deployed in small field trials. Wernstadt, Davidsson and Johansson (2007) introduce an agent-based approach with a tiered optimisation structure quite similar to the PowerMatching City project in the Netherlands (Bliek, et al., 2010). Kensby, Truschel, Dalenback (2015) examined the potential of residential buildings in Gothenburg, Sweden as thermal energy storage by exposing them to various charge and discharge cycles and monitoring the deviation in internal temperature. The data generated is used to develop a degree-hours metric of estimating internal temperature deviations providing an arms-length estimate of the impact of demand shifting.

Almost all the papers surveyed mention the importance of respecting consumer requirements for comfort however comfort is very difficult to define both for those trying to shift energy demand and consumers themselves. Some of the studies surveyed monitored internal temperatures in the controlled homes (Karkkainen, et al., 2004) while for others the only means of determining the acceptability of any temperature deviations was to wait for tenants to complain (Kensby, Truschel, Dalenback, 2015). Controllability, generally, is an area where district heating has been found lacking in the past therefore new innovations in this area must deliver for consumers.

A number of authors have presented the results of simulation exercises in the areas of DH optimisation and demand flexibility, a range of which are reviewed by Olsthoorn, Haghighat and Mirzaei (2015). Guelpa and Verda (2016) deploy an optimisation approach to explore the potential for peak demand reduction on the DH network in Turin through utilising building thermal inertia in order to avoid peak demand caused by overnight setback temperatures.

The percentage of space heating provided by district heating in the UK is currently very low, 2% according to Aecom (2015). In recent years the UK Government has recognised the role that DH can play in providing a flexible energy vector for the future energy system and with their encouragement a number of new schemes including the one which hosted this field study have been developed. The UK DH market is therefore growing rapidly.

This paper presents unique insights on the potential for flexible demand to be delivered on UK district heating networks. Although the trial population is small and cannot provide generalized results, the combination of monitored data and questionnaire responses has created a rich dataset which provides lessons for the design of future pilot programmes and the future deployment of demand shifting technology in the UK.

The Field Study

Trial Cohort and Intervention

The trial cohort consisted of 28 homes connected to a DH network in the South West of England (Rose, Harding, Carter, & Sweetnam, 2016). All participating households were recruited on a convenience basis from the respondents to an advertisement sent to the customer base of the district heating network operator.

The homes that make up the cohort are newly built, between 2010 and 2015, and cover a range of sizes and typologies from apartments to larger four bedroom detached units. The homes typically have an EU Energy Label rating of ‘B’ according to the sales material for the development. Detailed information, required to calculate the time constant of the dwellings, is not available however as they are relatively well insulated one can surmise that they have a time constant nearer the upper end of the range discussed previously (28h – 108h). The participating households were all owner-occupiers and full-time employment.

As part of the trial the homes had a new Danfoss Heat Interface Unit (HIU) installed together with three heat meters. One was installed on the primary side of the HIU and two on the secondary side. The meters on the secondary side measured domestic hot water consumption and space heating. The HIU was controlled by a relay device, connected wirelessly to PassivSystems Home Energy Management System. Participants could control their heating via a tablet, mobile phone or web portal. Domestic hot water (DHW) is provided instantaneously by the HIU, with temperatures and pressures controlled mechanically. Figure 1 gives an overview of the equipment installed in the homes. No active heat storage was installed in the homes, instead the thermal inertia of the building fabric and buildings systems is used to facilitate demand shifting.

[Figure 1 Near Here]

One internal temperature recording has been made which was intended to be placed on a wall in the main living space, at ~1.1m high, out of direct sunlight. Unfortunately, there is no way to verify the installation team placed the sensors as instructed.

Trial Design

The experimental design for the project included three different control phases, *Timer/Thermostat Mode*, *Optimizing Mode* and *Active Shaping* as illustrated in Figure 2. These are explained further below.

[Figure 2 Near Here]

Due to time restrictions, it was not possible to measure household heat demand prior to the installation of the PassivSystems HEMS. In order to get an understanding of the likely demand profiles of the homes prior to the project, initially, all participating homes were configured in *Timer/Thermostat Mode*. During this period the HEMS was configured to simulate the operation of a simple timer and thermostat for an initial period of 3-4 weeks. Demand during this period is unlikely to exactly match the pre-trial patterns for a number of reasons; in the first instance, weather patterns will have varied. In addition, households were invited to input their occupancy times and target temperatures using PassivSystems user interface which encourages consumers to indicate the times they require warmth as opposed to the times they wanted their heating system to operate, an important distinction that is likely to have caused settings to differ from their pre-trial configuration. Finally, the system was configured to provide pre-heating which was not a feature of the replaced controllers.

After the baseline period the predictive control capabilities of the HEMS were enabled. We have used the term *Optimising Mode* to describe this period. The predictive control algorithm uses a learned model of the home combined with forecast external temperatures and the households indicated target temperature requirements to deliver thermal comfort while minimising energy use.

The predictive control algorithm also has the ability to take into account time varying energy costs and/or respect demand constraints, which determine maximum or minimum demand for a given period. These can be passed to the HEMS via the internet. We term periods where the demand coordination service was active and demand constraints were in place *Active Shaping.* Periods of *Active Shaping* were determined and enabled/disabled remotely by the research teams. Where Active Shaping is in place demand constraint signals are calculated remotely by demand coordination software and passed to half the of the controllers alternately in a crossover experiment. No altered behaviour was required of the homeowner and they were not aware whether their controller was in Optimising or Active Shaping mode.

The crossover design aimed to provide a controlled test of the demand shaping algorithms. A stable roommate algorithm (Irving, 1985) was used to pair the 28 trial home according to the similarity of their overall energy profiles and a member of each pair were randomly assigned to group A or group B. Throughout the experimental period A and B were alternatively chosen as the ‘active’ or treatment group who received demand shaping signals while the other group formed the control group.

The demand shaping signals were generated using a coordinated control algorithm that aimed to reduce demand peaks and optimise the operation of the district heating network. As DHW was provided instantaneously, the basic aim was to construct a set of constraints that ensured space heating demand did not coincide with DHW demand so that total demand was as flat as possible while respecting the thermal comfort requirements of the participants and ensuring energy consumption was not excessively increased. The algorithm incorporated a simple techno-economic model of the DH network that returned the cost of delivering a given heat demand profile. This allowed the minimum cost combination of load profile and total energy demand to be found.

Questionnaires

Three short questionnaires (5 – 10 questions each) were administered during the field trial in order to gather participant feedback, as indicated in Figure 2. These questionnaires were carried out using the ‘Google Forms’ survey system with participants invited via email. Response rates were 75% and 78% for the first two questionnaires but dropped to 46% for the final questionnaire. Questions were related to the user experience provided by PassivSystems controls; the participant's experiences of the demand shaping and on their experience with the use of controls as well as other topics reflecting the commercial interests of the companies involved in the trial. While the latter class of questions are of limited academic interest the dataset of questionnaire responses provides important insights that help to illuminate the monitored data and vice versa.

Analytical Methods

The HEMS, alongside the additional heat metering, provided a range of data points for analysis. The various sensors are listed and described in Table 1.

[Table 1 Near Here]

As all homes had a broadband connection and the project team were pro-active in rectifying data collection issues, the data gathered in the field trial was 99% complete therefore only limited data cleaning was carried out, as follows;

(1) The heating control and target temperature data which is a state signal is processed to produce a 'square wave' time series.
(2) The data is interpolated to 2 minute time intervals using linear interpolation.
(3) The three control phases, including the active periods for demand shaping, are marked.

A number of analytical approaches have been used to understand the impact of the demand shaping. The principal approach used in summarising the data is 'profiling'.

Where profiles of internal temperature or energy demand are presented they have been derived using the following data processing steps:

(1) The data was interpolated onto a 15 minute grid by taking the mean value over these time slots.
(2) All weekday/weekend days for the homes & date range of interest were grouped together.
(3) For each home the mean value and the upper and lower deciles for each of the 15 minute time slots within the home's dataset were calculated. On completion of this stage the processed dataset contains a weekday and weekend profile of mean internal temperature and a profile of the upper and lower decile of internal temperatures and so on for each of the variables of interest.
(4) The final step is to calculate the mean of all of the mean values and deciles of the upper and lower decile values for each time slot over all of the relevant homes in the cohort. The outcome is a unified temperature or demand profile for each of the tree trial periods.

As the available sample is relatively small this approach allows the influence of the interventions made on the mean behaviour of the homes and the range of behaviours to be explored without undue influence of outlying data. This approach is facilitated by the use of the crossover trial design whereby periods of Optimised Control and Active Shaping occurred in tandem and therefore the homes in either group have experienced identical external weather conditions over a given period. This does not apply where data from the Timer Thermostat period are presented. The profiles are presented as graphs for interpretation alongside some basic metrics;

Where mean energy demand is presented on these graphs it is calculated as the simple mean of the mean profile without accounting for the impact of changing external temperatures. Where mean internal temperature is presented it is calculated as the simple mean of the mean profile with no account of the potential impact of changing external temperatures as described above.

The load factor is calculated from the mean profile. The load factor is a ratio that summarises the 'flatness' of a demand profile, calculated for a given day, *'X'*, as shown in equation 1 below. When considering network capital costs the load factor provides a useful summary of the ratio between the network peak size and the total volume of heat sold.

$$Load\ Factor_{\ DAY\ X} = \frac{Mean\ Demand_{DAY\ X}}{Maximum\ Demand_{DAY\ X}} \tag{1}$$

In order to estimate the impact of demand shifting on space heating demand that is normalised for the influence of external temperature the following steps are taken.

(1) Beginning with the interpolated data produced by step (1) above we calculate the total daily space heat demand for each home and the daily mean external temperature.

(2) The daily data for individual homes are grouped by each of the three trial periods.

(3) A linear fit is calculated between the daily space heating demand and daily mean external temperature.

(4) The line of best fit is used to predict the space heating demand at 7°C external for each trial period. This value is chosen as it is the coldest value that appears in all three periods.

Finally, A number of 'case studies' or plots of the raw data are used to illustrate points made throughout the discussion, particularly where it facilitates comparisons between participants questionnaire responses and activity in the homes as evidenced by the measured data. In this case selected portions of the ‘2 minutely’ data is presented in its raw form with supporting annotations. These annotations aim to explain the actions of the HEMS device and interventions made by the household.

The questionnaire data has been analysed using simple statistical methods and is presented in graphical form.

Results & Discussion

This section begins by examining the impact of the interventions on the internal temperature and demand profiles of the participating homes. Figure 3 presents living space and total heat demand (as measured on the network side of the HIU) profiles.

[Figure 3 Near Here]

The influence of the controller and the demand shaping is made most apparent in the internal temperature profiles of the dwellings. Firstly, the introduction of the optimised control leads to a reduction in the mean measured temperature accompanied by an increase in the range of recorded temperatures, particularly at the lower end of the scale. The introduction of active demand shaping, and the use of the thermal inertia of the home for energy storage, increases the mean slightly and reduces the range. It also has a clear influence on the shape of the profile, visible on the temperature evolution graph, reducing overnight cooling and pre-heating in the afternoon between 12 and 16hrs.

Turning to the demand graphs, on the right-hand side of Figure 3 there is a clear change in the pattern of demand when the optimised control is introduced, principally more overnight operation and a more gradual ramp up of demand in the morning. The outcome of this is that the morning peak is reduced and the load factor is increased from

0.29 to 0.41 before any active demand shaping. When the demand shaping is introduced there is a further, small, reduction in morning and afternoon peak demand and a small increase in the load factor to 0.44.

[Figure 4 Near Here]

Figure 4 disaggregates the heat demand between space heating and hot water. Isolating the space heating demand reveals the influence of the demand shaping signals more clearly. There is a clear reduction in demand during the morning and afternoon peaks with consequent increases in demand during the overnight and afternoon periods. There is a significant difference in the total demand between the timer-thermostat period and the two later periods, this is due to cooler external temperatures as discussed below. Hot water demand, meanwhile remains relatively consistent throughout.

While the demand constraints have successfully reduced space heating demand around the times of peak hot water demand, it is not completely eliminated. This is a result of the algorithm design with aims to balance increases in energy demand and impacts on comfort conditions for the dwelling occupants with benefits for the network. While it is possible to evaluate success in shaping demand by plotting energy and temperature profiles, determining success in other areas is more complex.

[Figure 5 Near Here]

Data covering the Timer Thermostat period was gathered prior the beginning of the crossover experiment between Optimised Control and Active Shaping and therefore fewer data points are available and external conditions have varied. Figure 5 presents the fit between space heating demand and external temperature used to calculate normalised demand at 7°C in order to take this variation into account. The analysis shows an increase from 8.9kWh/day at 7°C in the Timer Thermostat period to 9.2kWh/day at 7°C in the Active Shaping period. This indicates the energy cost of the improvement in load factor discussed previously is a 3% increase in space heating demand. This is a very small impact which is within the margin of error for this type of analysis given the limited length of the trial period.

The following sections will explore these issues in more depth, presenting portions of monitored data from individual homes and discussing the response of the HEMS to the demand constraints and interventions from the participants. Feedback from the participants, in the form of their questionnaire responses will be presented alongside this data.

Table 2 explains the annotations used on the case study graphs. Each of the case studies present temperatures and energy data. The upper graph shows predicted temperatures which are for the initial model run, '0' with no constraints in place and for the final run, 'F', with the constraints. The measured 'Zone 1 Temperature' is also shown alongside the target set-point temperature. The lower graph shows predicted heat demand at '0' and 'F' alongside the demand constraint and the measured space heating delivered.

[Table 2 Near Here]

Figure 6, is an example of the effect demand constraints have on the control regime. In this case a demand peak of 7kW is predicted in the morning and 6kW in the afternoon. Demand constraints are calculated that aim to halve the demand peak during the morning and evening periods.

In the area marked ‘Pre-Heat’ the controller raises the internal temperature, storing heat so that the morning target temperature can be met while respecting the constraint. At 6am the internal temperature is ~17°C whereas the model had predicted it would be at 15°C in the absence of constraints. During the middle of the day the internal temperature deviates from the prediction somewhat and therefore demand is overestimated around the period marked ‘Over Estimate’. Later in the day however the controller is forced to disobey the constraint, at ‘Disobeyed’, in order to maintain the internal temperature within ±1°C set for the experiment.

[Figure 6 Near Here]

Thermal comfort is a complex combination of activity/metabolic rate, clothing, air and surface temperatures as theorised by Fanger (1970) and is also affected by external conditions, perceptions of control factors addressed by deDear and Brager (1998) in their adaptive model. In order to address these complexities, it is likely that a range of values tailored for individual households would be required. For this set of experiments a set of temperature bounds of ±1°C were enforced during the participants ‘In’ periods in order to limit impacts on thermal comfort. This simple approach is adopted while acknowledging the need for further research in this area.

While some insights can be gained from the monitored data this does not explain the participants motivations and priorities when it comes to their heating system. The first questionnaire asked the participants whether they prioritise cost, comfort or control. The responses reveal a broad spread of concerns among the options offered: (a) having the lowest possible energy bills, (b) having your home at a comfortable temperature, (c) having ultimate control over the operation of your heating system. This highlights the complexity of designing demand flexibility systems that can satisfy the entire spectrum of potential customers.

Of the available options (c) was most frequently chosen by the survey respondents. Demand shifting using the thermal inertia of the home, intuitively, means that the heating system may operate at unusual times or in an unusual manner and therefore may cause consumers to feel they are not fully in control.

Questionnaire 3 posed a number of questions in this area firstly asking whether or not participants had noticed unusual operation. Here, the responses indicate that ~70% of respondents noticed unusual heating activity during the night time While this may be a cause for concern among participants it may be possible to alleviate these concerns by managing the expectations of scheme participants. Where thermal comfort is affected this indicates the limits of demand shifting in this manner are being reached to.

Regarding awareness of unusual operation of their heating system, the participants noticed that the radiators were warm and they indicated that they had felt slightly or uncomfortably warm, as shown in Figure 7. Although our aggregated analysis of the data indicated a very small increase in internal temperature, it appears that instances of high temperatures have occurred and these have coloured the views of participants. Analysing the maximum temperatures recorded during the trial reveals 3 homes that have exceeded 26°C at some point however it is not possible to correlate these with the participants perceptions.

[Figure 7 Near Here]

Finally, participants were asked to indicate their perceptions upon noticing unusual operation. The most popular responses here were around energy wastage and system malfunctions. These indicate a lack of understanding among the occupants of the overall aim of the demand shaping, while they have correctly identified increased energy use this is necessary to deliver network benefits. In this case, the research team made a conscious decision not to inform the participants precisely when the demand shifting would occur. In future commercial schemes providing better explanations to scheme participants and managing their expectations is likely to be very important for the successful roll-out of demand management schemes and indeed, when presented with incentives the majority of customers indicated they would participate as discussed below.

It is important to note at this point that participants could have interrupted the pre-heating at any point by adjusting the target temperatures however we have been unable to identify an instance of this in examining the monitored data. Instead, Figure 8 illustrates the impact of an 'in-the-moment' change involving an upward adjustment to a household's target temperatures on the demand shaping process. Around the periods marked 'Over-Ride', beginning at ~17:00hrs the target temperature is boosted to 22ºC resulting in unplanned spikes in energy demand.

[Figure 8 Near Here]

Systems such as PassivSystems' HEMS encourage increased levels of interaction by providing user friendly user interfaces. In Questionnaire 1, participants were asked *'How easy was it to use your old controls…'* to carry out a number of common actions and provided their response on a four-point scale from ‘Very Easy’ to ‘Very Difficult’. Questionnaire 2 posed the same question in relation to PassivSystems HEMS. Figure 9 presents the results which indicate that participants found the HEMS significantly easier to use.

[Figure 9 Near Here]

The consequence of this is to make the households thermal comfort requirements, expressed as their target temperatures, more unpredictable. The advantage of HEMS systems is that aggregate analysis of data may make it possible to predict and account for this behaviour across a large cohort of households.

Finally, on the topic of encouraging participation, Questionnaire 3, attempted to identify a value at which the respondents would be willing to take part in a demand response scheme, the results are summarised in Figure 10. Despite the inconveniences identified in previous responses a majority of respondents would participate for £5/month and over half indicated they would participate for £2/month. Both of these values are likely to be less than the network benefit of participation which, of course, will vary depending on the type of network considered.

[Figure 10 Near Here]

Conclusions

This paper has presented results from a field trial of demand shifting technology deployed on a district heating network in the UK. While this is a pilot trial and it is not possible to make statistical generalisations from the results, as far as the authors are aware this is the first field trial of this type to be reported in the UK and among a small number that have been carried out worldwide.

Our analysis of the measured data has shown that the introduction of PassivSystems HEMS has led to a reduction in peak demand due to the weather compensation and optimisation features of the control software. Introducing active demand shaping, which primarily aimed to use building thermal inertia to avoid simultaneous space and hot water heating lead to a further reduction in the demand peak. The total impact is an increase in load factor from 0.29 to 0.44. We have estimated that the energy cost of this improvement is a 3% increase in demand which is within the margin of error for the analysis.

On UK networks which have inherited a timer thermostat model of heating control, or in other areas where there is a 'cultural norm' of night time heating setback, this change to the demand shape and reduction of peak demand can deliver operating and capital cost savings that may be shared with consumers. For networks where space heat is already delivered more continuously, the approach described here may present opportunities to both reduce energy demand, by providing some overnight cooling, and manage load factors by avoiding co-incident heating and hot water demand. Overall network impacts have not been explored in detail by this study, and are a subject for further research. It is likely, for example, that in the case of larger networks where consumption patterns are highly diversified the usefulness of demand shifting will be diminished.

As Meulen (1988) pointed out 't*he ultimate objective of district heating is to maintain a suitable indoor climate in the connected buildings and not to supply heat'* and therefore an important aim of the project was to assess impacts on internal temperature and gather participant feedback. While our analysis of the measured data indicated a very modest increase in internal temperatures caused by the demand shaping the feedback received from the occupants still indicated some concerns. This is in contrast with many of the studies highlighted earlier that have assumed significant freedom to alter internal temperature, in some cases ±2°C.

This difference between measured impacts and perceived impacts is perhaps one of the most significant findings of this work. There are a number of possible explanations for this discrepancy. While the analysis presented here has focused on the mean demand profile it is possible that individual cases of high temperatures have occurred and that these have ‘coloured’ the views of the questionnaire respondents. In addition, the trial participants knew they were participating in an experiment and therefore may have been more aware of the behaviour of their heating system than typical consumers.

On this basis, we recommend careful consideration of the information provided to participants when deploying these systems commercially. Clear explanations of how the system operates, how this may differ from their expectations, what they can do to ensure their comfort requirements are met and, importantly, the benefits that their participation brings both to the overall network and to them as individuals should be provided to avoid raising concerns and reducing participation. It is encouraging that when presented with a scenario where they received a modest reward for taking part in demand shifting such a high proportion of the field study cohort indicated they would be willing to participate.

Future work in this area will focus on three areas. Firstly, the results of this field study and others has revealed the importance of both better understanding and delivering thermal comfort requirements. This includes work on helping consumers more accurately express their requirements through the user interface and better delivering these requirements while taking into account radiant temperatures, activity, external conditions, perceptions and the other determinants of thermal comfort. Secondly, larger scale deployments of the demand shifting technology are required to deliver statistically significant measurements of its impact. Finally, a modelling effort is under way that aims to develop a stock model that will allow impacts to be evaluated at the UK scale.

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Tables

Role	***Description***
Zone 1 Temperature	Air temperature in the main living space (used for control).
External Temperature	External temperature recorded at a local weather station.
User Setpoint Zone 1	The user's target temperature.
Heat Meter Flow Temperature	The 'primary' flow temperature from the district heating network to the home.
Heat Meter Return Temperature	The 'primary' return temperature from the home to the district heating network.
Heat Meter Overall Energy	Energy use by the home, measured on the district heating network side of the HIU.
Heating Circuit Pipe Zone 1 Temperature	The 'secondary' flow temperature from the HIU to the radiators.
Boiler In Pipe Temperature	The 'secondary' return temperature from the radiators to the HIU.
Heat Meter Space Heating Energy	Energy use measured on the radiator circuit.
Combi Cold Water In	The temperature of fresh water entering the HIU.
Combi Cold Water Out	The temperature of domestic hot water leaving the HIU.
Heat Meter Hot Water Energy	Energy use measured on the domestic hot water circuit.

Table 1: Monitored Data

Pre-Heat	Indicates points where the demand constraint has led to pre-heating
Over Estimate	Indicates instances where demand has been overestimaxted by the algorithms.
Disobeyed	Highlights areas where the demand constraints have been disobeyed because it was necessary to stay within the temperature boundaries or because of an occupant override.
Over-Ride	Indicates occupant interaction or over-ride behaviour.

Table 2: Explanation of Annotations on Case Study Graphs

Figure Captions

Figure 1: Monitoring Equipment

Figure 2: Field Trial Timeline

Figure 3: Zone 1 (Living Space) Temperature and Total Heat Demand Profiles

Figure 4: Space Heating and Hot Water Demand Profiles

Figure 5: Space Heating Demand, External Temperature Relationship

Figure 6: Sample day showing the effect of demand constraints on the control regime

Figure 7: Questionnaire 3 - Question 2 Responses

Figure 8: Sample day showing the impact of an 'in-the-moment' change to a household's target temperatures on the demand shaping process

Figure 9: Questionnaire Responses: Controls ease of use

Figure 10: Questionnaire 3 – Question 4 Responses

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i The thermal time constant of a building results from the interaction of the thermal mass of the dwelling and its rate of heat loss. See Merji et al (2013) for a detailed explanation.