Appendix 5 Demand Flexibility at Fintry

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1.1. Introduction

The shift emphasis from a centralised to a decentralised energy system is an inevitable outcome of the low carbon transition. As the share of decentralised technology in the energy system grows, the technical and economic efficiency of incumbent network management arrangements is likely to be disrupted, allowing new operating paradigms, technologies and market entrants to emerge. However, this process is moving more slowly than the technical change that is stimulating it, held in abeyance by underpinning regulation governing market entry and subsequent access to revenue. It is imperative therefore that innovation in market composition and regulation be supported such that plausible methods of operation can be discussed and trialled. The Smart Fintry project is one of a group of projects being conducted in the UK to explore how markets can be developed that reflect the increasing localism associated with energy supply. The importance of local energy was alluded to in the recently published Scottish Energy Strategy[1]. This called for Innovative local energy systems, stating that the Scottish Government would empower our communities by supporting the development of innovative and integrated local energy systems and networks. The Smart Fintry project has sought to explore technical, regulatory and economic issues associated with the development of innovative, integrated local energy systems. Smart Fintry is a community project based in the Stirlingshire village of Fintry pioneering a new way of trading and charging for electricity so that householders and businesses can buy their electricity directly from nearby renewable energy generators, using the existing electricity grid infrastructure. The aim is to reduce both electricity costs and carbon impacts.

This paper describes a number of technical analyses that have been conducted in furthering the overarching aims of the project. It takes as its starting point an assumption that a local energy market will seek to optimise local supply demand balancing. From a data analysis perspective, two critical aspects are apparent when furthering an understanding of what local balancing might mean;

a) To what extent can local demand and supply be forecasted?

b) To what extent can local demand flexibility be characterised?

The HWU research group have prepared a paper describing the forecasting methodologies that have been applied in Fintry. This paper describes the research activity that has been undertaken to characterise demand flexibility. It also reports on an investigation to determine the load flexibility that may be made available by legacy electric storage systems.

1.2. Characterisation of Demand Flexibility

The methodology adopted to characterise demand flexibility opportunity is described in Figure x below. The features of the demand dataset complied from the metered Fintry dwellings was first selected. A number of different statistical clustering approaches were then investigated and

[1] Scottish Energy Strategy: The future of energy in Scotland, Scottish Government, December 2017

customers segmented based on these. The characteristics of the dwellings (construction, dwelling type, energy system and demographics) were then elicited for each segment from survey report provided by the Fintry Development Trust.

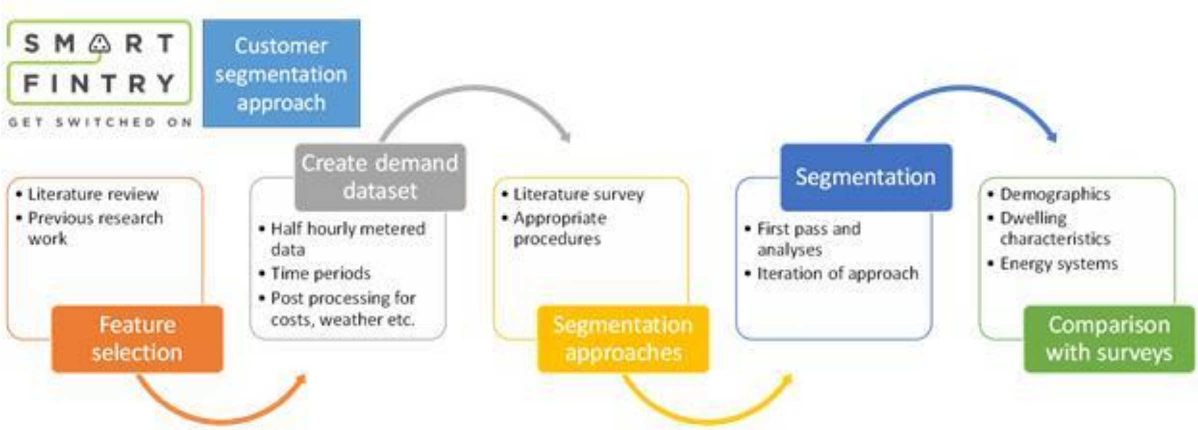

Figure x; Smart Fintry Customer Segmentation Approach: description

1.2.1. Feature Selection

Demand response is taken here to mean an intentional electricity usage adjustment to price changes or incentive payments by consumers. A critical aspect in understanding the local community demand response is determining the features of demand profiles that can be used as proxies for demand response availability. Data-based segmentation of electricity customers is attracting increasing research and institutional attention as a consequence of the widespread installation of advanced metering equipment that measures and stores individual customers' temporally precise load information.

Jang et al (2016)[2] suggested segmenting customers according to a range of variability indices that were used as proxies for demand response opportunity. This methodology was followed here, with a range of features deemed pertinent to residential demand response opportunity devised.

Previous work carried out by the HWU Research Group has explored behavioural and actuated demand response capability of a Scottish Community[3]. Householders were exposed to a dynamic electricity tariff that varied each day depending on forecasted availability of surplus electricity from a local wind park. A limiting level of response was found that was appropriated

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[2] Jang, D., Eom, J., Park, M.J. and Rho, J.J., 2016. Variability of electricity load patterns and its effect on demand response: A critical peak pricing experiment on Korean commercial and industrial customers. Energy Policy, 88, pp.11-26.

[3] http://www.origin-concept.eu/system/files/ORIGIN%20Final%20Report.pdf accessed March 2018

to the maximum level of flexibility available with existing, non-smart appliance stock. The magnitude of this limiting response was comparable to that reported in similar trials[4]. The proportion of locally generated renewable energy (RE) was increased by 5.8% during the trial. A key feature of those dwellings that provided the largest demand response was their total consumption level, with higher levels of consumption affording greater demand response opportunity. The increase in local RE consumption found through incentivised behavioural response was more than doubled when actuated systems, triggered using the same forecasting metrics were deployed. These utilised the flexibility afforded by electric boilers connected to thermal stores that supplied space heating and domestic hot water to dwellings. These findings indicate two features that can be used to characterise demand response opportunity; namely total consumption and timing of consumption. If consumption patterns can be revealed that are likely to lie outside active occupation periods then they are likely to signify the presence of storage capacity in a dwelling.

In addition to characterising the opportunity for demand response in a dwelling (or cluster of dwellings) it is also important to consider other features that may have economic relevance to energy suppliers. Identifying consumers who have demand response opportunity may represent the greatest societal benefit to a local energy market concept. However, suppliers are currently economically incentivised to retain consumers with flat profiles, with no load shift potential as they will then pay less in network and wholesale costs. This consideration was furthered in this analysis by the availability of a partial cost stack describing the cost of supply for a typical winter's day[5]. This considered the costs in supplying a customer that change throughout the day assuming half hourly settlement, i.e. the static cost elements are omitted.

[4] Carmichael R., Schofield J., Woolf M., Bilton M., Ozaki R., & Strbac G. (2014) Residential consumer attitudes to time-varying pricing, Report A2 for the" Low Carbon London" LCNF project: Imperial College London, Tech. Rep

[5] Data supplied by Good Energy for a typical winter's day in 2017 using data from National Grid (TNUoS & BSUoS); SSE (DUoS); EMR (Capacity Market)

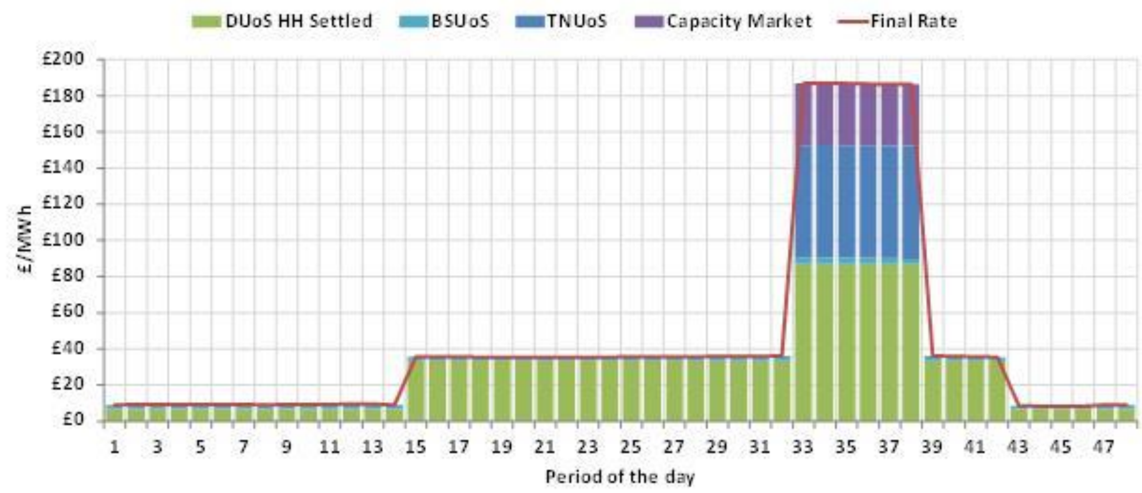

Figure x; Variable Cost Stack for residential Customer Supply- Typical Winter Day 2017

1.3. Demand Dataset

The demand dataset used the half hourly metered data (kWh) from participating Fintry residents, monitored by the Energy Assets metering equipment. The following particular aspects of the dataset were observed for each of the features defined in the Table below.

Feature No	Feature Parameter	Unit	Candidate Monitoring Period
1	Time variant consumption	kWh between different periods of the day during the candidate monitoring period	February 2017
2	Load variability & consumption	Principal component analysis using 3 features of the demand data over the candidate monitoring period; (a) Average daily load factor, (b) Average daily coefficient of variation and (b) total consumption	Jan-Dec 2017
3	Cost of supply	£/kWh supplied during candidate monitoring period	Jan-Mar & Oct-Dec 2017

Table x; Summary of features used to segment customers

Feature 1: Night-time consumption

This feature used a dataset for the period February 2017. During this period 60 dwellings returned half hourly electricity consumption data for more than 80% of the time period. Of these, four dwellings were excluded because they either had rooftop PV systems or they had dual electricity meters with either an economy 7 or economy 10 tariff. Consumption periods were defined to match the cost periods broadly indicated in Figure x.

Feature 2: Load variability & Consumption

This feature used a dataset for the full 2017 calendar year. During this period, meters from 88 dwellings returned consumption data for at least 10% of the year; 46 dwellings returned data for the full calendar year. The discrepancy was largely due to the pace at which new meter installations were rolled out. However, of the 56 dwellings who were returning data on the 1st January 2017, 10 did not provide data for the full calendar year with 5 communicating for less than 60% of the year. This raises substantial issues surrounding data efficacy if computational procedures that use metered data are linked to tariffing arrangements. A growing research community are investigating issues associated with missing half-hourly meter data in this regard. The dataset used here considered the 76 dwellings that had data availability for at least 40% of the year.

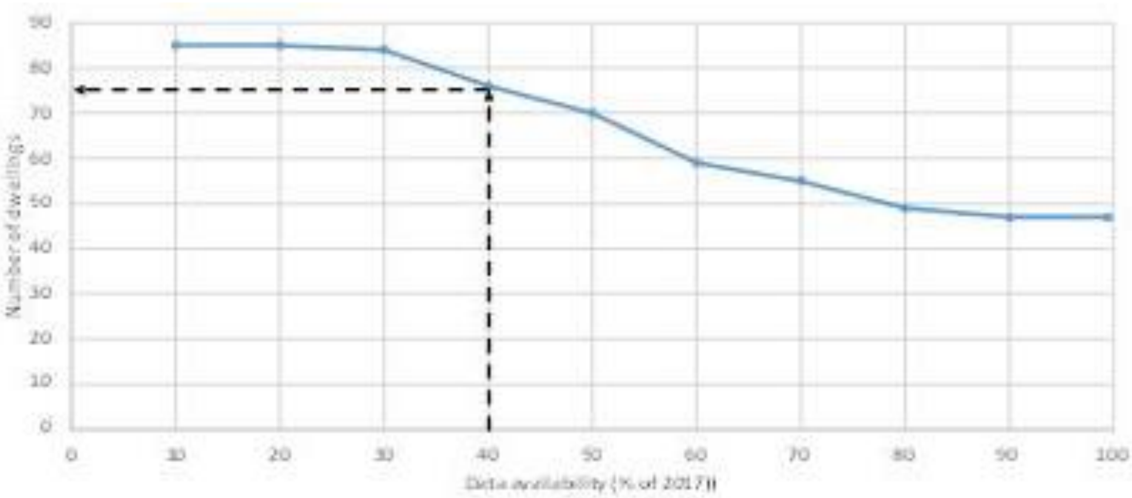

Figure x; Fintry Dwellings - Annual data availability 2017

The scheduled roll out of metering to participating dwelling ensured that even dwellings with 40% coverage would return data that bridged the seasons. Therefore, the requisite level of variation would be provided for the clustering process.

Three features were computed to describe load variability & consumption.

- The annual average daily load factor. The load factor is a commonly used metric in the electricity industry to express load profile variability. It is given by the fraction of average daily demand to peak daily demand.
- The annual average of the coefficient of variation of daily demand
- The total annual consumption

Principal component analysis was used to combine these features and simplify the subsequent clustering process.

Feature 3: Cost of supply

A subset of the annual dataset using only the months January-March and October-December was created to estimate the winter time cost of supply. The cost stack described in Figure 2 was applied to each half hourly consumption value and a total supply cost and consumption level calculated for the six month period. The cost of supply for each dwelling was then expressed as a p/kWh metric.

1.4. Segmentation Approaches

Conventional approaches to characterise domestic electricity used statistical methods to produce profile classes. These are then aggregated and post corrected, using for instance forecasted weather variables to provide regional or national demand estimates. Their derivation is based on an average time series from a subset of monitored dwellings which are then used to describe all consumers assigned to the profile class. Typically seasonal load profiles are produced.

A number of engineering approaches have been developed over the last decade, often in response to the paucity of domestic electricity consumption demand datasets that are available for research. Techniques have included the use of descriptive statistics, regression, pattern recognition and bottom up modelling using appliance signatures. These methodologies tend to produce highly bespoke datasets whose usefulness beyond the experimental bounds of their origin are limited.

An explosion of interest has emerged over the last decade in the use of data mining techniques to elicit information regarding electricity profiling. A detailed discussion of the suitability and application of these techniques is beyond the scope of this paper but extensive reviews have appeared, see for instance (Wang et al, 2014[6] ; Rajabi et al, 2017[7] and Jin et al, 2017)[8].

A popularly deployed technique for clustering consumers based on specific features of load profiles is k-means clustering. This describes a methodology which seeks to organise observations within a dataset into a number of different clusters based on the similarity between it and the mean of the assigned cluster. An initial number of clusters and their associated centres are initially selected based on a selected feature of the data. Once initial clusters and associated have been assigned (based on statistical parameters in the whole dataset), the dwellings can then be assigned to their nearest cluster based on the distance between the object and the cluster centres. This is an iterative operation, carried out until a statistically significant distance between resultant clustered data is achieved. Successful k means clustering would see the variance between clusters approaching the variance of the entire dataset. For detailed procedural guidance see for instance Al-Wakeel & Wu (2016)[9] .

[6] Wang, Y., Chen, Q., Kang, C., Zhang, M., Wang, K. and Zhao, Y., 2015. Load profiling and its application to demand response: A review. Tsinghua Science and Technology, 20(2), pp.117-129.

[7] Rajabi, A., Li, L., Zhang, J., Zhu, J., Ghavidel, S. and Ghadi, M.J., 2017, August. A review on clustering of residential electricity customers and its applications. In Electrical Machines and Systems (ICEMS), 2017 20th International Conference on (pp. 1-6). IEEE

[8] Jin, L., Lee, D., Sim, A., Borgeson, S., Wu, K., Spurlock, C.A. and Todd, A., 2017. Comparison of Clustering Techniques for Residential Energy Behavior using Smart Meter Data. Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States).

[9] Al-Wakeel, A. and Wu, J., 2016. K-means based cluster analysis of residential smart meter measurements. Energy Procedia, 88, pp.754-760.

1.4.1. Customer Segmentation

Feature 1: Time variant consumption

This approach clustered dwellings into four groups based on their consumption in each of the time periods described in Section2. The lowest consumption group in each time slot was assigned the datum 1 and the highest 4. The clusters are shown in Figures x for each time slot. A selection of key findings are summarised below:

- The ratio of demand dataset variance and cluster group variance was high for each time period (>90%). This indicates high statistical separation between the clusters.
- A dwelling with high electricity consumption during the period 19h30 to 07h00 is may indicate consumption that is largely disassociated with demand. Twelve dwellings appeared in the highest consumption clusters. Of these, 10 were found to have heat pumps cf a total of 13 dwellings in the data set. 1 dwelling had electric oil filled radiators and one dwelling was found to have an oil boiler. This is a potentially useful, data led result that identifies with a relatively high degree of accuracy the presence of a space heating device with demand flexibility. All clustered dwellings in the green and blue groups were found to be detached dwellings.
- Six dwellings were clustered in the lowest consumption for three periods and the highest consumption group for the peak cost period. These dwellings would have the highest cost of supply as their proportionate peak consumption was the highest.
- Of the 56 dwellings included in the dataset, 21 were always clustered in the lowest consumption group regardless of the time slot. 1 dwelling was always clustered in the highest consumption class.
- Twelve dwellings were assigned to clusters 3 and 4 during the period where the cost of supply was highest. Of these 9 dwellings were placed in the highest consumption cluster in at least 2 other periods.

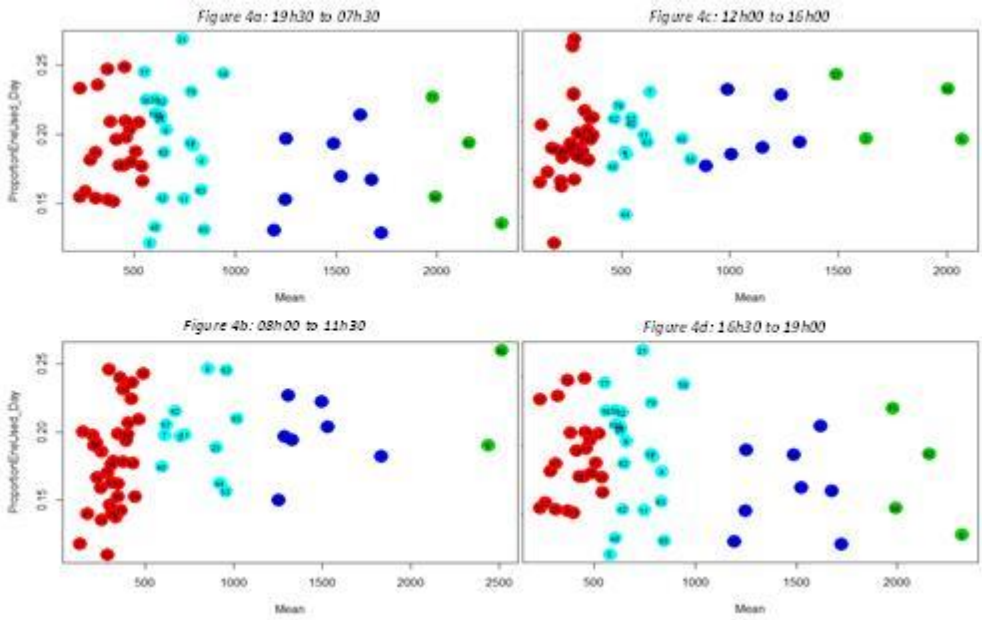

Figure x; k Means clustering for time of day consumption level in February 2017

1.4.2. Load variability, consumption & cost features data treatment and clustering

Clustering using these features are considered together here as their outcomes are all predicated on aspects of consumption and load variability. Three individual analyses were conducted:

a) Load variability & consumption

The first used a single feature created using principal component analysis of parameterised data representing the three features described in Table 2 (load factor, coefficient of variation and total consumption). This single feature captured all of the variance contained in the combined data. Analyses of the clustered groups indicated a high degree of separation with clusters found to be relatively tight with variance distinct from each other based on the variance found in the datasets from each feature (Figure 5a).

b) Load variability, consumption & cost

The second analysis applied the same statistical approach to load variability, consumption and cost features. The cost data itself is an indicator of load variability with higher per kWh costs arising as a consequence of higher peak time consumption. Analyses of the clustered groups indicated a satisfactory degree of separation with some overlap particularly between clusters 1 and 4 (Figure 5b).

a) Cost

The third analysis used the cost feature on its own with variance therefore only displayed on a single axis. Overlap between blue and turquoise clusters is evident (Figure 5c). Site 56 was found to be an outlier. This was not a function of data coverage and additional analysis and repositioning of the dataset is required to be performed in a subsequent analysis.

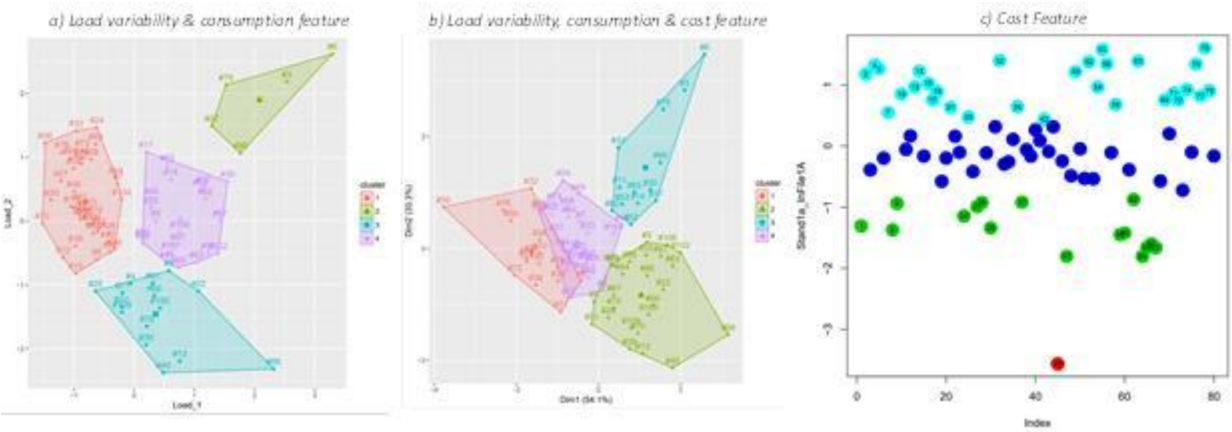

Figure x; Cluster groups for each feature selection analysis

Load Variability, consumption & cost feature findings

- An average load profile was constructed for each cluster using the half hourly consumption data for a January 2017.
- Only three clusters were evident for the analyses using the cost feature. Cluster 1 only contained a single dwelling which did not return data for January.
- Clearly distinct average load profiles can be discerned for each cluster, for each feature analyses
- The influence of level of consumption can clearly be seen in each analysis. Additional work will be carried out on the dataset to identify features that remove consumption as an influencing factor. This will allow load variability and timing of consumption aspects to be investigated more thoroughly.
- That said, differences in load variability were found. They were less prominent with the load variability & consumption feature. The load factor of the average load profiles were found to be 0.69, 0.89, 0.78 and 0.86 for the Cluster Groups 1-4 respectively.
- By comparison, the cost only feature provided a more distinct graduation of variability returning 0.44, 0.61 and 0.74 for Cluster Groups 2-4 respectively. This reflects the influence of consumption during periods 33-38 where cost of supply was more than four times that for other periods in the day.
- Similarity of clustering using the three features was conducted by assigning the terms high, medium-high, medium and low to each of the respective cluster groups based on consumption level.

- Sixteen dwellings were similarly assigned by all features. Twelve of these were in the low category, three in the medium-high category and four in the high category. This again stresses the distinctive nature of the cost feature.
- A number of characteristics were selected from the participant surveys to investigate whether the clustering process revealed information about the household. These were heating system type, whether occupants were working or retired and the number of bedrooms (the latter as a proxy for dwelling floor area which wasn't recorded).
- The clustering process did not yield any significant, discernible household characteristics based on the selected criteria. Feature selection here did not focus on specific times of the day unlike the previous approach. The small data sample (only 46 of the 76 dwellings retuned survey information) and its relative homogeneity (84% of those dwellings that returned information were detached for instance) may have also been a causal factor.

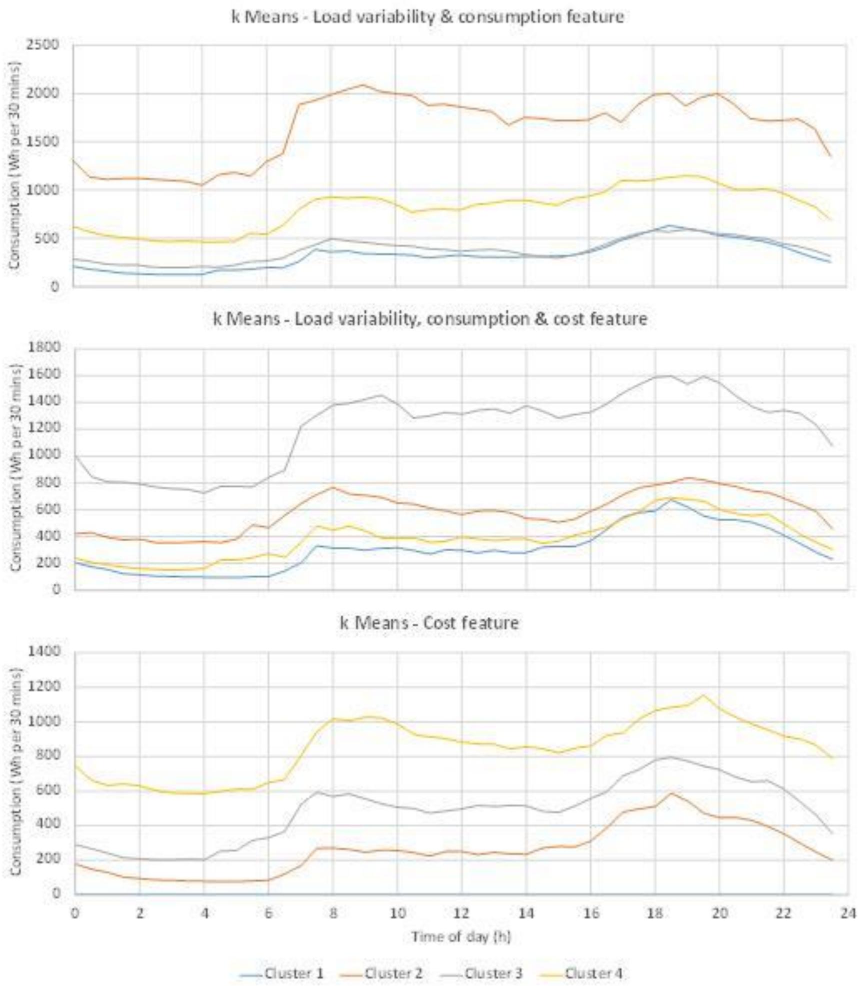

Figure x; Average load profiles for each cluster group January 2017

1.5. Load flexibility of legacy electric storage heaters

In the UK, the most prevalent method of electric space heating is electric storage heaters of which there are approximately 1.7M (6%) dwellings. In Scotland, the numbers are proportionately higher in comparison to total dwellings with c0.3M dwellings (12%). This increased proportion is reflective of the higher proportion of dwellings that are not connected to the main gas grid in Scotland.

The assignation of heating systems to dwellings in Fintry was conducted by analysing a survey conducted by FDT containing 217 responses (greater than 60% of the community) (Figure 1). The proportion of dwellings with electric storage heaters was found to be 20%, higher than the national averages as would be expected of an off-gas grid community.

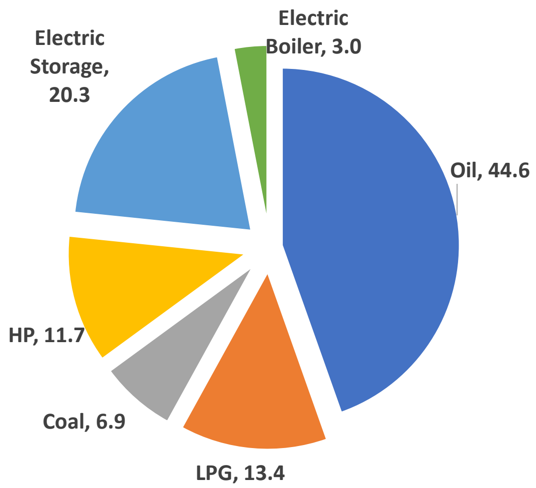

Figure x; Distribution of heating systems in Fintry

The approximate average electrical load per dwelling associated with storage heaters has been estimated as being 8kW with a total (nominal) storage capacity of 56kWh. In Fintry this would translate into an approximate flexible load of 480kW and a capacity of 3.36MWh. This is significant in the context of local RE sites included in the Smart Fintry study (50kW and 110kW of solar-PV and wind capacity respectively) and significant even if the output from the c1MW AD plant were to be included.

Electric storage heaters have, traditionally been controlled using signals that emanate from outside the dwelling. Their potential for providing strategic over-night load growth to assist with utilisation of nuclear baseload plant coupled with a need to avoid network impact of simultaneous switching led to the deployment of the Radio Teleswitch systems in the 1970's. Whilst this functionality has been eroded due in part to regulatory change to electricity markets, storage heaters in an estimated 0.5M UK households are still controlled using this methodology.

Reported studies that have queried householder satisfaction with their space heating systems indicates that the majority of electric storage heating households are relatively satisfied with their heating system (68% satisfied vs 25% dissatisfied). However, satisfaction levels are lower than for mains gas households and householders are less likely to feel warm. For instance, the 2013 Scottish House Condition survey found that 42% of electric heating households in Scotland did not feel their heating kept them warm enough. This can be compared to 23% dwellings heated using hydronic heating systems fed by gas boilers.

In summary, electric storage heaters offer a significant, flexible load which has historically been controlled using external objective functions. However, the capacity of these systems to satisfy thermal comfort requirements is questionable. Given that this is their primary requirement, a study was carried out to investigate heat delivery from electric storage heaters using data from a number of Fintry dwellings.

Night time temperature inflection

The performance efficacy of electric storage heaters is predicated on insulation levels of the storage cabinet. If levels of insulation are inadequate then stored heat will leak from the cabinet into the dwelling at times more aligned to charging periods rather than the desired thermal comfort period. Two distinct charge periods for storage heaters in Fintry were found 23h30 to 07h00 and 15h30 to 17h30. Leakage from the cabinet to the dwelling would be most evident during overnight charging when external temperatures were low and dwelling internal temperature would otherwise be falling.

Figures x & x show the average internal temperature of two dwellings in Fintry recorded using Tiny Tag thermocouples located in the living room during the period March to May 2017. These profiles are compared to average electricity consumption for the period. A clear night time temperature inflection point can be seen in both dwellings that occurs after heating charge periods. This is a clear indication of leakage having occurred from the units.

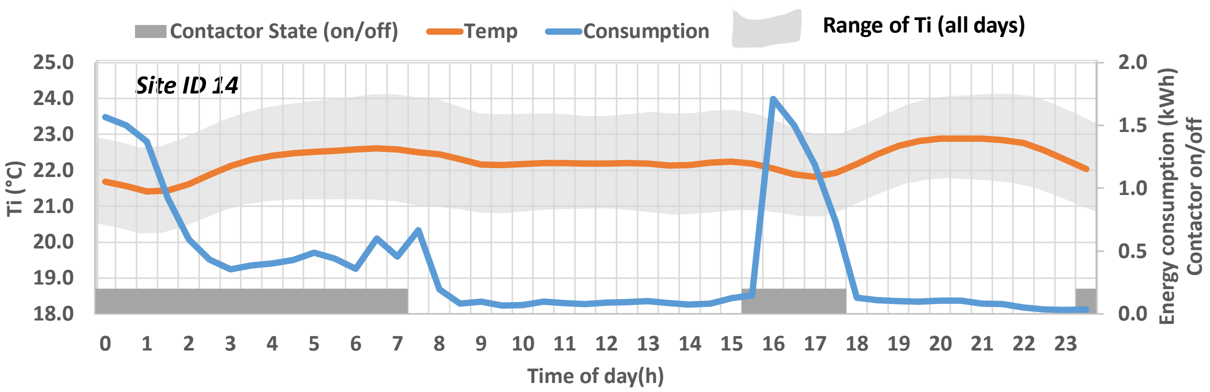

Figure x; Average Internal temperature of Site ID 25 between March and May 2017 cf average electricity consumption

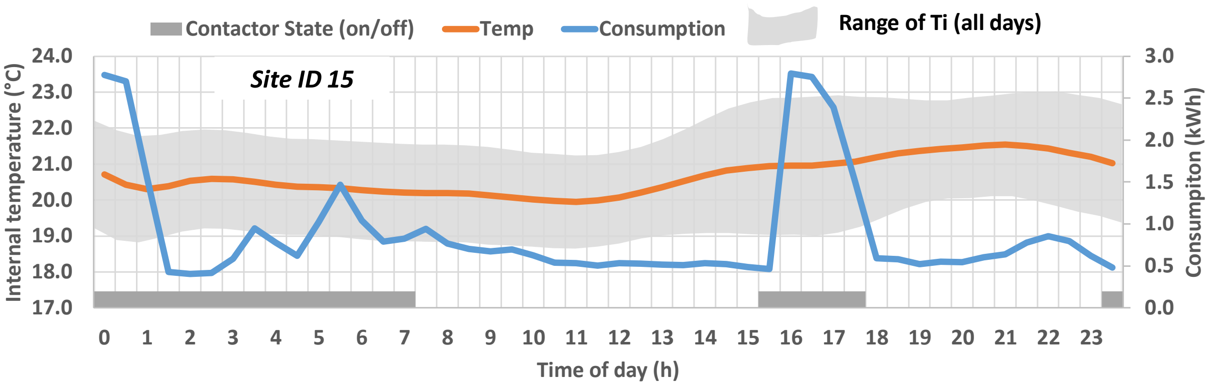

Figure x; Average Internal temperature of S Site ID 15 between March and May 2017 cf average electricity consumption

The range of internal temperature at 68% CI (one $\sigma\bar{x}$) was 2.5°C and 3.0°C for Site ID 14 & 15 respectively across the 24 hour period. This is perhaps surprising as the monitoring period included May and solar gain would have been expected to create additional temperature variation during the afternoon. The tightest period of control was during late afternoon and early evening when the electric storage heaters are effectively operating as an on-demand resistance heater.

Thermal comfort delivery

A small number of the participating dwellings had meters that also returned an internal temperature. This data was less precise than the tiny tag data, only recording temperature as a whole number. The internal thermal profile of two of these dwellings was compared, one heated using electric storage heaters (Dwelling 93) and one heated using a ground source heat pump (Dwelling 97) during October and November 2017. The influence of space heating system on the temperature inflection point can also be seen on this temperature record (Figure 4). In the dwelling heated using electric storage systems, the peak night time temperature occurred at 02h30 and was almost 1°C higher than the temperature at 08h00.

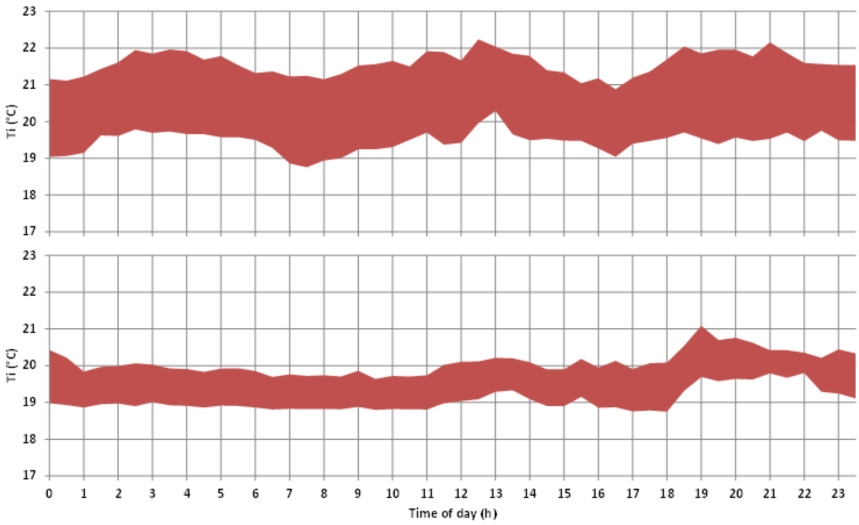

Figure x; Average Internal temperature range for Electric storage (Dwelling 93; top) and GSHP (Dwelling 97; bottom)

During the monitoring period, the range of the temperature profile in the electric storage system in dwelling 93 was more than twice that delivered by the ground source heat pump in dwelling 97 (Figure 5). These dwellings are considerably different in dwelling, construction type and size (Table 1). It might be expected, from their descriptions that the dwelling 97 would be more difficult to heat consistently

Parameter	Dwelling 93	Dwelling 97
Occupancy	1 retired and 1 unemployed	2 retired
Type of dwelling	Semi-detached	Detached
Floor area	93 m2	335 m2
Wall construction	Timber frame (insulation assumed)	Solid wall
Glazing type	Double glazed throughout	Mostly double glazed
Heating system	Electric storage	GSHP

Table x; Dwelling characteristics for two sites

It should be stressed that these results should be treated with caution. They may, for instance be a function of sensor location rather than a true reflection of the heat delivery precision of the respective energy systems. They are, however, worthy of further assessment, both in terms of data analysis (longer time periods, more dwellings) and through site visits to ascertain other factors that may be have a material impact.

Degree day correlation

It was assumed that dwellings heated using electric storage systems would show a high level of correlation between daily heating degree days and daily electricity consumption than. This correlation was plotted against total electricity consumption for the period disaggregated by type of heating system. Forty dwellings which returned a consistent monitoring period between June and December 2017 were assessed. A simple Pearson's Correlation coefficient was derived between the total electricity consumption during the monitored period and daily heating degree days. No statistical difference was found between the type of heating system and the level of correlation. A primary determinant of the scale of the correlation was the overall consumption level (Figure x). This indicated a more or less linear relationship between consumption and degree day correlation up to a value of circa 4000kWh after which the level of correlation plateaued.

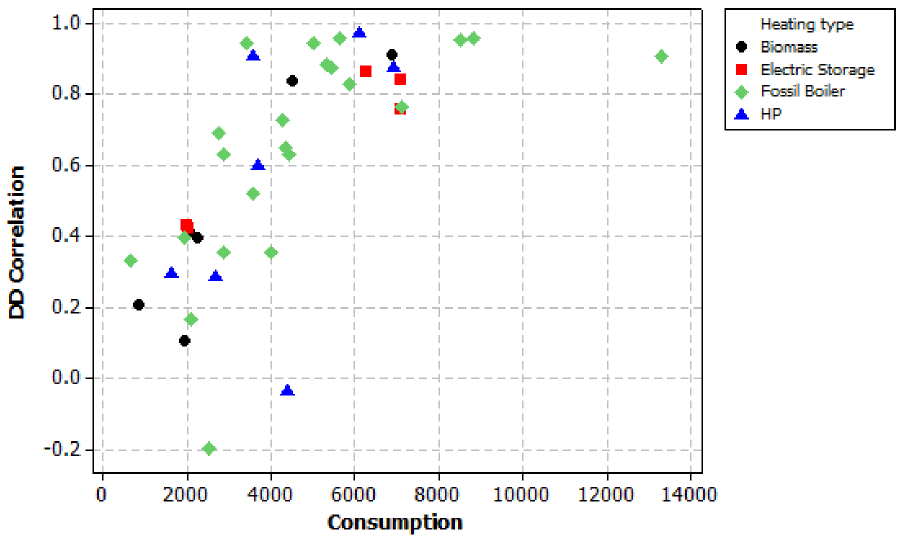

Figure x; Correlation between daily degree day correlation and total consumption over the monitored period

1.6. Conclusions and further work

- The number of dwellings with clean data that incorporates electricity consumption and thermal comfort temperature is too small in this sample to make conclusive statements

- However, the value of having these two datasets to describe dwelling energy systems is imperative if sensible, dwelling centric conclusions are to be reached regarding the identification of a dwelling as a candidate for load control.
- There are a number of well-rehearsed descriptions of the inadequacy of legacy electric storage space heating systems in meeting their primary objective, i.e. provision of thermal comfort to the dwelling.
- The results found here, all be it from a small sample reach similar conclusions. Poor insulation leads to heat leakage from the unit. To a large degree then these units should be viewed primarily as point heaters and control should shift from a storage paradigm to one that seeks to locate the charging period as close to thermal comfort periods as possible.
- The research group have previously investigated methods of defining when these thermal comfort periods may occur. This has applied Hidden Markov Modelling approaches to half hourly electricity consumption data to determine likely periods of active occupancy. These approaches in combination with monitored internal temperatures would result in well-defined forecasting of thermal comfort requirement.
- These forecasts could then be used to impose improved control regimes on legacy electric storage heating systems to deliver better thermal comfort outcomes for residents. This would be a major step forward for the 0.3M consumers who use these as their primary space heating systems.
- The metering infrastructure coupled with this control development would allow this to be achieved. Diversity of load could be maintained within these thermal comfort improved charging envelopes using conventional approaches.
- Load flexibility from legacy electric storage heating systems should only be explored once these improved control regimes have been deployed as a secondary control feature.
- Initial results from clustering approaches using k-means has returned potentially useful results. Initial, simple methods of feature selection using the timing of half hourly metered electricity consumption has identified, from a dataset of 59 dwellings those that are detached and use heat pumps as their primary source of space heating. These may be represent dwellings that have a high potential for load shifting.
- Further feature selection processes that investigated consumption, load variability and cost functions were carried out. These brought forward distinct load profiles for different customer segments.
- Clustering using the cost feature identified three customer segments that could be defined as being high, medium and low with respect to supplier cost of supply. This reflected both consumption level and the proportion of consumption that occurred during periods 33-38 where cost of supply is highest.
- Further feature selection will be conducted by the HWU research group to investigate these clustering approaches more extensively. These will seek to isolate aspects of load variability and investigate different time blocks to determine whether demand response flexibility opportunity can be quantified for the participating dwellings.