THE USE OF SIMULATION TO OPTIMISE SCHEDULING OF DOMESTIC ELECTRIC STORAGE HEATING WITHIN SMART GRIDS

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ABSTRACT

Smart grid technology will allow electricity networks to use distributed storage in the form of domestic space heaters and hot water tanks to help balance supply and demand. A major test-bed for the concept has been deployed in the Shetland Islands, UK. This paper reports on the use of dynamic simulation to explore different approaches to scheduling such a system. It requires modelling at the level of the entire electrical network, as well as of detailed heat transfer processes within individual appliances, and of the feedback between these. It is shown that these storage devices could reduce curtailment of wind generation by up to 20%, without affecting occupant amenity, provided that the control system logic was capable of handling individual instructions to many devices.

INTRODUCTION

The transition to a low carbon electricity network is constrained by the high cost of installing energy storage at the scale needed to maintain network stability and balance intermittent or constant supply with fluctuating demand (Strbac *et al* 2012). Distributed, small-scale storage in the form of heat is a cheaper option (Foote *et al* 2005), and electricity utilities have long used domestic space and water storage heaters on overnight tariffs to help shift peak loads. Today, 20% of domestic electricity consumption in the UK comes from the 1.7 million households with electric storage heaters and the 1.3 million with electric hot water tanks (DECC 2012). The scope to expand this through occupant-controlled, price-based demand side response is attracting interest both from the markets (Ofgem 2013) and from researchers (Finn *et al* 2011, Kelly *et al* 2014).

Another possibility is to use smart grid technology that allows dynamic load shifting to be controlled centrally by the utility. This has been modelled with grouped electric vehicle storage by Ghofrani et al (2012) and by Howlader *et al* (2013) for groups of smart houses with grid side supercapacitor storage. Broeer *et al* (2014) used data from the Olympic Peninsula smart grid deployment to model how individual controllable domestic appliances in 112 houses could contribute to integrating wind power.

A major test bed for this concept is now being established with the Northern Isles New Energy Solutions (NINES) project on the Shetland Isles. Shetland, with a population of 22,000, is located 160 miles from the UK mainland and is serviced by a power system that is not connected to the UK national grid. Network stability constraints mean that only one 3.7 MW wind farm can currently be accommodated. The distribution network operator, Scottish Hydro Electric Power Distribution (SHEPD), is therefore installing an Active Network Management (ANM) system together with smart space and water storage heaters across a large estate of houses (SHEPD 2011) with the intention of allowing a significant increase in wind generation capacity. The ANM system monitors the stability of the electrical network, calculates the maximum stable wind generation and, if necessary, curtails wind generators in response to demand fluctuations. The ANM also produces a charging schedule for the storage heaters, aiming to minimise CO_2 emissions by minimising curtailment of wind and smoothing the power output required from conventional generation (Dolan *et al* 2013).

THE DOMESTIC STORAGE DEVICES

The heaters (Figure 1) can accept input power at variable but discrete levels every 15 minutes and relay back status information. They are also able to respond automatically to changes in electrical frequency, shutting down charging when the frequency drops below an acceptable level and increasing it when the frequency rises.

a) b)

Figure 1: The Quantum domestic storage devices: a) space heater b) hot water tank .

The space heaters are better insulated than earlier models, allowing fan-assisted active output regulation by occupants. They also incorporate a maximum temperature cut-off for safety and a minimum temperature switch-on setting to ensure occupant comfort.

As a partner in NINES, the University of Strathclyde carried out a series of modelling tasks for different elements of the new technology, to assess how effectively each would work at both device and system level. A field monitoring programme was also deployed, commencing with prototype technology in 2011. In addition to providing insights into how the technology works in practice, these data were used to calibrate and validate models.

Initial findings from the field monitoring, reported by Clarke *et al* (2013), established that although the heaters worked well from the occupants' point of view, they were less effective for the network operator. All devices frequently charged during unscheduled periods, or stopped charging when scheduled to do so. They also made use of only part of their available storage capacity, around 35% on average. This was largely due to the charging approach deployed, but concerns about possible adverse impact on occupant amenity and costs limited the extent to which it was possible to experiment with alternative schedules in the field.

Several different approaches to scheduling were therefore studied using simulation when applied at two levels as follows.

1. Detailed thermodynamic modelling of fixed schedules with various timing and power levels, applied to individual houses with different construction type, occupancy and thermal comfort preference. This resulted in some general lessons about which types of charging schedule work well and which do not.
2. A power system optimisation for the whole network, assuming a deterministic underlying heat demand for the whole estate of houses with smart storage. This study produced an optimal charging schedule from the power system perspective.

These studies have shown that:

- it is possible to construct charging schedules that can be followed by the heaters in an individual house to a high extent, without impacting occupant amenity;
- dwellings are not particularly sensitive to the timing or level of the power input, accommodating load shifting even over 48 hours, provided that the energy delivered is roughly in line with demand, and that the heater controls are configured not to compete with the central control;
- for the occupants, centrally controlled schedules can result in less overheating and less energy use than with traditional teleswitching; and
- for the network operator, having flexibility to schedule storage heater charging over 24 hours enables higher load factors on 15 MW of new wind generation, and reduces fossil fuel use at the power station (Gill and Kockar 2013).

The next step is to investigate whether the system as a whole can work as intended. This paper presents the interim findings for simulations that examine how individual dwellings respond to centrally imposed schedules, how this changes if scheduling flexibility is extended to 48 hours, and how this response affects the utility's ability to apply flexible scheduling. While the study context is Shetland, the outcomes are applicable elsewhere.

MODELLING APPROACH

The challenge is to model how a high-level system covering the entire electrical network interacts with individual devices whose ability to follow instructions is influenced by myriad detailed thermal processes taking place within individual dwellings. The approach taken was to carry out the modelling in stages using different systems.

1. A heat demand forecast is made for the entire estate at 15 minute intervals by a forecasting tool using bottom-up simulations of individual houses.
2. The aggregated demand forecast is input to a power system model, which produces a charging schedule for the estate that is optimal for the network as whole.
3. The estate schedule is then decomposed into charging schedules for individual houses, and input to detailed thermal simulations where each storage heater is modelled in an explicit manner.
4. The individual house models produce profiles of the actual heater charging profile and these are then summated to show the impact on the network.

EVALUATION CRITERIA

An important criterion for network operations is the degree to which the heaters follow the schedule instructions. A schedule following index SFI is defined as:

$$SFI = 1 - (US + ND)/(TC) \tag{1}$$

where US is unscheduled charge, ND is scheduled charge not drawn, and TC is total scheduled charge.

The overall benefit is measured by the reduction in fossil fuel generation due to lower curtailment of wind generation. This is then compared to a baseline fossil fuel generation and wind curtailment over 2 years with no smart storage.

From the occupant perspective, there are two key success indicators: maintaining comfortable room temperatures, and managing costs. The total energy demand is used here as a proxy for costs – although if scheduling flexibility gives enough of a benefit to the operator it would be possible to adjust the tariff such that this is not the case.

ESTATE DEMAND FORECASTER

The demand forecasting model operates using a library of space and water heating demand profiles for individual houses, generated by the simulation programs ESP-r (2013) and DHWcalc (2012). By appropriate aggregation, the forecaster predicts a 24 hour ahead profile for groups of 50-100 houses based on the temperature forecast for the following day.

Implementing the forecaster required constructing a number of ESP-r dwelling models typical of those comprising the Shetland estate. A high amount of internal detail was included to cater for different configurations of storage and direct heaters. The storage heaters were represented as a combination of constant, low power, fixed output and a thermostat-controlled, high power output corresponding to the passive loss and fan-assisted output cases respectively.

One-year simulations at 15 minute intervals were run for each of 34 combinations of building geometry, construction and heater configuration that best represented the intended rollout estate. Each such reference house model was run for a range of day types, occupancy levels and preferred indoor temperatures, giving 408 dwelling and day type combinations. For each variant, average daily demand profiles were calculated for 1˚C increments in average outdoor temperature during winter and summer seasons. Separate profiles were made for space heating in living, hall and bedroom areas, where these contained storage heaters.

Each dwelling in the actual estate was mapped to one of the reference houses, based on its actual construction, layout and heater configuration. Occupancy patterns, indoor temperature preferences, and hot water demand were allocated statistically to each house so that the estate as a whole exhibited the behaviour reported in national statistics and in a number of large scale measurement programmes. All data were stored and manipulated by the EnTrak tool, a generic system to manage information associated with energy and environment issues. The forecaster and its underlying assumptions are presented in detail in Clarke *et al* (2013).

To generate a demand forecast, a set of reference profiles is selected from the database using the expected average external temperature. The profiles are scaled according to the ratio of floor areas in the actual and reference house. The profiles for each house in a group are then added to produce the aggregate 15-minute demand profile.

The forecaster was used to generate profiles for the rollout estate, for the years 2010 and 2011. An example of the daily space and water heating demand for a large estate of 1750 houses generated thus can be seen on Figure 2.

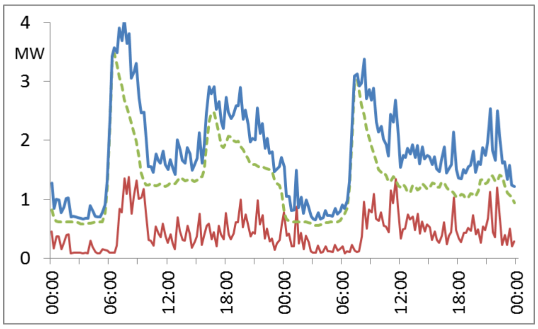

Figure 2: Heat demand profile (bold line) over 2 days for large estate, made up of space (dotted line) and water (narrow line) heaters.

POWER SYSTEM MODEL

The power system model covers the entire Shetland electricity network (Figure 3). The smart storage system at each network location is represented by the aggregated heat demand profile, total charging capacity and total energy storage capacity for the heater group. This underlying heat demand must be satisfied by providing electrical energy to the devices so that enough stored energy is available at each time-step to meet demand.

The power system model is an extension of the industry standard optimal power flow method, known as Dynamic Optimal Power Flow (DOPF) (Gill *et al* 2014). The objective of the optimisation is primarily to minimise the electrical generation from fossil-fuel plant and therefore reduce carbon emissions. This is achieved by charging heat stores with electricity at times of excess wind generation and so reducing curtailment of wind.

The DOPF model takes full account of the electrical characteristics of the 33,000 volt power network (overhead lines, undersea cables, transformers) and enforces all limits relevant to secure operation of the power system (maximum power flow through components, maximum and minimum voltage levels, maximum and minimum generator outputs). It also models electrical losses and reactive power flow as required by the voltage level of the network.

In addition to standard optimal power flow – which solves for a single point in time – DOPF creates a network model for each time-step within an optimisation and links those time steps with additional components used to model the flexibility provided by the smart storage devices.

The power system model was invoked using historical electrical demand and wind generation data for 2010, a year with low wind availability, and for 2011with high wind. Two levels of deployment of domestic smart storage were considered: 250

dwellings, corresponding to the current rollout plan; and 1750 dwellings, equivalent to replacing most of the current storage heating on the islands with smart devices.

An optimisation was performed over the two consecutive years, with 96 time steps in each 24-hour period: this models the day-ahead scheduling as implemented within the NINES project. The optimisation was then repeated over a 48 hour period with 192 time steps.

The output is a time-series of electrical charging instructions for the devices across the estate, which is optimal from the perspective of minimising fossil-fuel generation and is theoretically possible to implement. Figure 4 shows the ideal charging schedule for the same two days as the demand profile in Figure 2. It can be seen that optimising over 48 rather than 24 hours allows more wind to be used. In both cases however the overall shape is different to the demand curve.

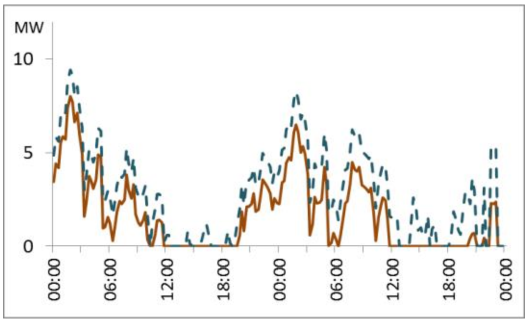

Figure 4: Ideal charging profiles for same 2 days optimised over 24 (solid) and 48 hours (dotted line).

The installation of ANM allows a significant increase in wind generation capacity to connect to the Shetland grid. It is estimated that this will be in the order of 10 – 15 MW, all of which may be subject to curtailment. The power system model was employed to define a baseline level of fossil-fuel generation with 15 MW of new wind capacity but no flexibility in demand. In this case, fossil fuel generation provided 301 GWh over the two years, and 16.7 GWh of potential wind generation is curtailed to maintain stability limits.

Table 2 summarises the results for the simulations representing combinations of low and high roll-out estates and 24- and 48-hour scheduling windows. It should be noted that the total electrical energy demand is constant throughout: reductions in fossil fuel generation are made because the storage heaters provide flexibility in the delivery of that energy.

The lowest total effect with 250 houses scheduled with a 24 hour window leads to a total reduction of 530 MWh in fossil-fuel generation. Increasing the scheduling window to 48 hours gives a 19% improvement.

The high rollout case, with 1750 dwellings, shows reductions of 2.47 GWh and 3.16 GWh for 24- and 48-hour scheduling respectively. In this case, 48 hour scheduling leads to a 28% improvement over 24 hours.

INDIVIDUAL HOUSE AND HEATER MODELS

In order to understand the key processes, the detailed impact of the optimised schedules was simulated for a small group of 3 houses. The selected dwellings each have very different characteristics (Table 1):

- a small flat in a newly converted traditional stone building;
- a timber semi-detached house with high level of insulation; and
- an older, detached block-and-render bungalow typical of much of the historical housing stock in Scotland.

Each house contains the appropriate space heater models, which could represent the main heat transfer processes explicitly:

- Separate charging of each of the three sections of the core at either 3 x 800 or 3 x 600 W;
- heat transfer from the core to the intra-heater air stream;
- uncontrolled heat transfer through the insulation to the room air; and
- fan-assisted heat transfer from the intra-heater air stream to the room air.

Electricity input can be varied at 15 minute intervals. Models are run for a full year with a 5- minute time step, to give a pragmatic balance between accuracy and processing time. The heater models had previously been calibrated against manufacturer laboratory test data and then validated against field measurements (Figure 5).

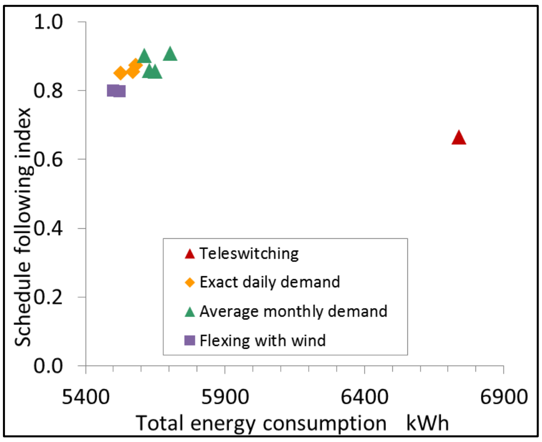

Figure 6: Total heat consumption and schedule following January to April under various fixed-timing charging approaches for the poorly insulated bungalow.

Previously reported studies had compared different approaches to energy delivery in the three houses between January and April. These included: standard Shetland teleswitching condition, where heaters charge at maximum during set tariff hours if they physically can; schedules which delivered the daily energy demand either exactly or approximately; and schedules which delivered up to twice the day's demand when the wind speed was high and zero if the wind was low. Each approach was applied at different power levels and at different times of day. However, within any one run the time of day was fixed. The outcomes consistently showed that there was very little difference in energy consumption or indoor temperatures with any of the active schedules, as long as these delivered cumulative heating demand over a 2 day period. In any dwelling, the worst schedule consumed only 1% - 7% more than the best. Teleswitching, however, consistently consumed significantly more energy and produced uncomfortably high room temperatures unless some form of charging cap was applied; in the worst case 66% more. Figure 6 shows the characteristic outcomes.

In order to provide a baseline for assessing the centrally optimised schedules, an annual schedule is generated for each house corresponding to the minimum total consumption scenario established previously. Energy delivery meets the demand each day exactly, at minimum input power and starting at 4 a.m. Note that while this results in the least consumption, the timing is not practically useful as it runs through morning peak electricity demand.

For centrally optimised scheduling, the charging instructions for each heater are deduced from the overall schedule produced by the ANM in two stages. First, an optimised schedule for each house within the group is generated by normalising the overall schedule over each 24 or 48 hour period, and then applying that shape to the total 24 or 48 hour demand. This is essentially the logic proposed for the Shetland rollout. Each house schedule is then translated into a series of commands for each heater such that the total power draw is as close as possible to that desired, but at one of the discrete levels available from the individual heater configurations.

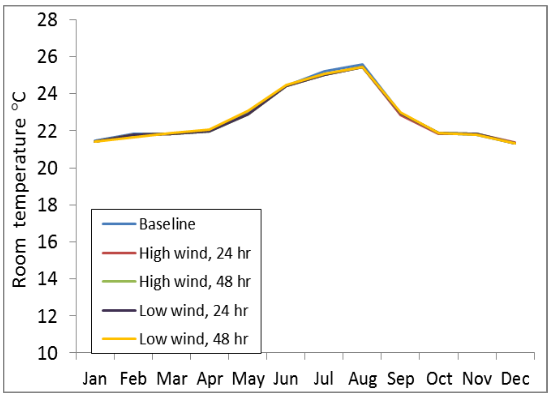

Figure 7: Median living room temperature during occupied hours, flat.

The simulations made so far have confirmed that changing the timing of the electricity input has minimal impact on room temperatures. As an example, Figure 7 shows the variation in monthly median living room temperature in one of the dwellings with the four different optimised schedules.

Figure 8 compares total demand and schedule following over the year for various input schedules by house. Once again, the difference between lowest and highest total consumption (including the contribution from direct heating) is negligible, never more than 2%, even when the ANM has optimised over 48 hours.

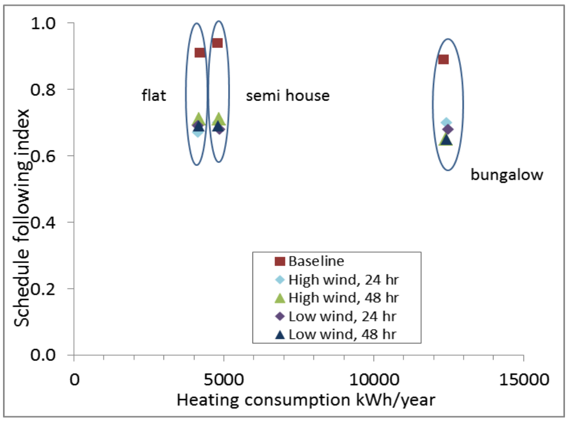

Figure 8: Total annual heat consumption and schedule following for the three houses with ANM scheduling.

The centrally optimised schedules do result in worse schedule following, in each case deteriorating from around 0.9 to 0.7 or less. In the flat and the semi-detached house, which are better insulated, there is not much difference between the high and low wind years or whether the optimisation is over 24 or 48 hours. For the poorly insulated bungalow, 48 hour optimisation does reduce schedule following further, to 0.65.

The group of 3 houses does perform better than the sum of its parts. In a one example, schedule following for the group rises from 0.68 based on individual houses, to 0.71 for the combined group. Total power draw is within schedule 50% of the time. The total energy drawn by the group over the year is just 2.6% more than scheduled: this is made up of 13% of scheduled energy not delivered, balanced by a slightly higher unscheduled draw.

An illustration of typical behaviour is given in Figure 9, which shows a close-up of scheduled and actual electrical consumption over a cold 48 hours: on the first day, the heaters charge largely as instructed. However, on the following morning there is not enough stored heat to kick-start the fan-assisted heating cycle so the heaters start to charge before schedule.

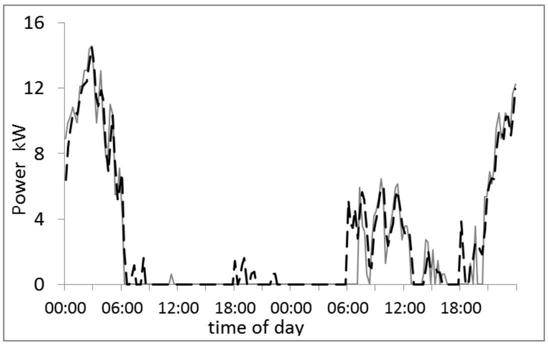

Figure 9: Power consumption of 3-house group over 48 hours, scheduled (solid) and actual (dashed line).

DISCUSSION

The current studies support previous findings that houses with smart storage heaters are able to accept widely flexible charging schedules without significant impact on the occupants. As long as the scheduled energy delivered is roughly equal to the cumulative demand, room temperatures and total heat consumption are largely unaffected even when the central schedule is optimised over 48 hours.

The ANM scheduling system requires a good quality day-ahead forecast for the storage heater demand in order to work correctly. The demand of each individual house depends on how many heaters there are and where they are in the building layout, as well as on the normal complexities of house size, construction, thermal mass, occupant behaviour and weather conditions. Such forecasts can best be made through dynamic simulation.

With the approach taken to date, the houses do not follow centrally optimised schedules exactly. The heaters' own internal safety and comfort settings override the central instructions if there is too much or too little energy in storage, leading to 10-15% of scheduled energy not taken, and a marginally higher amount being drawn outside schedule. When compared to the earlier studies, which showed only a small impact on schedule following with very different timings, this suggests that one cause of the deterioration may lie in the logic by which the central schedule was decomposed into instructions for the devices.

The centrally optimised schedule gives the correct amount of energy for the estate, taking into account the maximum charging capacity and storage capacity of all the heaters combined. Each disaggregated set of instructions must also meet these criteria for the devices included at that level, as well as fitting within the timing profile of the central schedule. However, the relationship between demand, charging capacity and storage capacity varies from house to house and even from day to day. Figure 10 shows how these relationships vary between the 3 modelled houses. Such variation is also typical in houses with traditional storage heating (Hayton 1994). With the simple scaling approach to disaggregation, houses whose storage capacity (in terms of average hours' consumption) is lower than average will fill up and run down faster than those with higher relative storage capacity. In each case, the excess or deficit energy drawn has eventually to be balanced out the other way, as the schedule is designed to deliver the demand exactly. Although at the group level there is some balancing out between over and under-draws, the three-house group result suggests that this diversification effect is likely to be small.

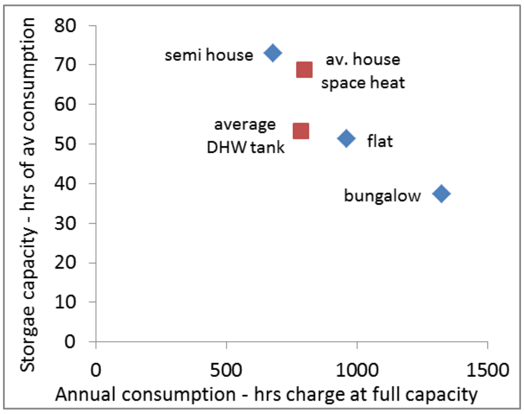

Figure 10: Comparison of relative annual consumption and storage capacity.

It should be possible in principle to develop a schedule disaggregation algorithm that is sophisticated enough to fulfil all the constraints of individual houses within the central profile. In practice however unless the scheduling logic in the deployment is very robust as well as very sophisticated, the expected wind curtailment benefit may not materialise. This area will form the focus for ongoing field monitoring as well as modelling work.

From the network perspective, the value of each new dwelling deployed on the system is subject to a law of diminishing returns. Although the overall reduction in fossil fuel generation was higher with more houses, the amount per house went down from 2.12 to 1.41 MWh per house. For a particular curtailment event smart heaters allow the level of curtailment to be reduced. If enough heaters are installed the curtailment is completely removed and further increasing the number of heaters is of no benefit in this particular event. Curtailment events are of different sizes, but as the smart heater rollout increases, there are less remaining events to managed and therefore a smaller return per heater.

Whilst 48 hour forecasting is shown in this study to produce improved system performance over the 24 hour scheduling, it must be remembered that this study makes the assumption of perfrect foresight for wind generation. For the deployed system to achieve the gains presented here, an accurate wind forecast for the optimisation period is required and the longer the period, the less accurate a forecast will be.

The approach of linking top-down modelling of an entire power network with bottom-up modelling of storage heaters and hot water tanks in domestic dwellings has given useful insight into the likely performance of a smart grid with distributed storage. This will be extended in future work for larger groups of houses and feedback within the two levels at shorter time scales.

CONCLUSION

Models have been developed to simulate the performance of what is among the most advanced smart grid deployments in the UK to date. The challenge of simulating the interaction of an entire power network with highly detailed processes in individual storage heaters within buildings has been addressed through running linked models in a series of steps. Studies to date demonstrate that the concept of using domestic storage heaters and hot water tanks as flexible storage for electrical energy is viable. Charging the devices to make best use of wind generation over any 24 or 48 hours reduces the time these have to be curtailed by up to 20%, and there is little resultant impact on occupant amenity. However, the challenge will be to ensure correct control logic to break down the overall schedule into sets of instructions for each individual device.

ACKNOWLEDGEMENTS

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Table 1: Characteristics of the three houses simulated with explicit heater models.

	House 1	House 2	House 3
Layout	Tenement flat	Semi-detached 2 storey	Detached bungalow
Floor area m^2	41	95	66
Wall construction	Thick stone	Insulated timber	Poorly insulated block and render
Heaters	2	3	4
Baseline heating kWh/year	4,198	4,784	12,318
Baseline storage heater demand/ charging capacity hrs/year	960	677	1324

Table 2: Reduction in fossil fuel generation for minimum and high levels of smart storage.

Deployment	Scheduling period	Fossil fuel reduction (GWH)	Reduced wind curtailment	Reduction per house (MWH)
250 houses	24 hours	0.530	3%	2.12
250 houses	48 hours	0.628	4%	2.51
1750 houses	24 hours	2.47	15%	1.41
1750 houses	48 hours	3.16	19%	1.80

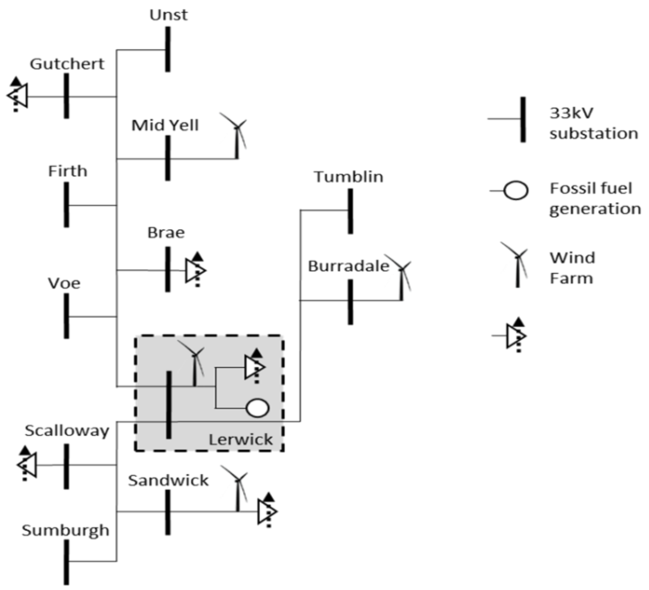

Figure 2: Shetland power system model.

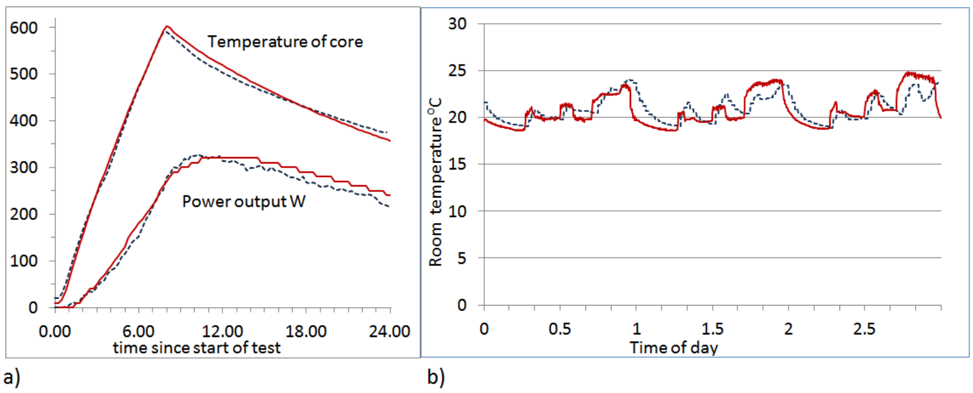

Figure 5: Calibration of heater models a) laboratory test data and b) field measurements Solid lines show simulation, dotted lines measurements.