

Paper 3

Managing complexity in the smart grid through a new approach to demand response

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Abstract

Adoption of weather-dependent renewable generation of electricity has introduced additional complexity to the challenge of maintaining a dynamic equilibrium between generation and electricity demand. At the same time the need for electricity to power heating and transport in place of fossil fuels will lead to congestion in distribution networks. Part of the solution will be to manage domestic electricity demand using signals between the smart grid and smart home, but this must be done in a way that does not provoke further instability. We use an agent-based model of household electricity consumption and supply to show how the complexity of domestic demand can be shaped allowing it to make a contribution to system stability. A possible role for this method in balancing conflicting interests between electricity consumers, suppliers, and distribution network operators is discussed.

Introduction

The variation of electricity demand in time and space is inherently complex because it arises from multiple human decisions that are themselves driven by complexity phenomena such as the chaotic patterns of weather or social clustering around a televised football match (leading to a demand peak at half time when kettles go on). However, safe and reliable delivery of gigawatts of electrical energy to satisfy this demand requires a precise and continuous dynamic equilibrium to be maintained between electricity generation and demand. This has been achieved successfully for about 100 years with a simple engineering solution that responds to temporal changes in demand with more or less fossil fuel input to the prime mover. Changes are detected and tracked by the shift in alternating current frequency that arises as generator rotation is slowed by an increasing load or accelerated by a reducing load. Spatial variation is addressed by generous sizing of distribution networks so that they can always handle the peak demand that can reasonably be expected at any location.

This mature paradigm must now change, driven by two factors. The first is the adoption on a large scale of renewable energy resources such as wind and solar photovoltaic generation which share some of the temporal variability properties of demand and cannot be controlled except by discarding some of the valuable energy they would otherwise produce. These resources are also far more geographically dispersed than conventional large scale generators. The second factor is increasing demand due to electrification of transport and space heating, motivated by the need to replace consumption of fossil fuels. This increase is not yet apparent, but a doubling of demand by 2050 is expected through policy action (DECC, 2011:6). Simply expanding distribution capacity to match this increase would be very expensive - Pudjianto, *et al.* (2013:83) predict a cost of £35bn for the UK. This expense could be substantially reduced if demand can be locally smoothed at the timescale of a day so that cables and transformers whose capacity is limited do not always have to support any possible peak. The “smart grid” is an epithet for the evolved electricity system that is needed to respond efficiently to these two challenges. The difficulty these present is illustrated by the potential within the existing system for small deviations from equilibrium to grow, propagate and cascade into catastrophic failures such as occurred in 2003 over part of North America.

In this paper we focus on one of the main issues in the design of the smart grid, the method by which electricity demand can be made subject to some degree of control. Because the supply side now has some of the complex variability previously limited to demand, controllability must be introduced on the demand side to enable the dynamic equilibrium to be maintained. Any method for achieving this (known generically as demand response) should also be capable of smoothing localised demand peaks to enable distribution networks to support the additional load. However the expectations and needs of consumers will continue to present complex patterns of demand making this problem, as recognised by Elliot (2010:14), a prime topic for complex systems modelling. Having undertaken such a modelling investigation, we have identified a method that satisfies these requirements.

Signals and Responses

In order to influence demand, a central authority responsible for maintaining equilibrium, known as the system operator, must be able to provide a signal to consumers indicating when electricity use is desirable or undesirable. In practice the system operator’s role is often mediated by an electricity market and a retail electricity supplier who transmits the signal to the consumer. There must also be

an agent, human or automatic, to change electricity consumption in response to the signal in a way that is predictable to the system operator and electricity supplier. The essence of the problem is therefore to specify the signal, identify the agent(s) that will respond to it, and characterise their behaviour.

The research performed so far has tended to employ a price signal, because the human response to price is reasonably well understood and such signals are already employed in a limited way by the industry. However, the price elasticity of electricity demand is quite small - in a review of 15 trials Faruqi and Sergici (2010:216) found a reduction in peak demand of about 2%-6% could be achieved routinely. Given the modest financial gain and possible inconvenience from switching off any individual appliance this is not surprising. This has led to a variety of experiments with automated “smart home” devices that respond to the price signal by seeking to minimise the consumer’s cost for operation of appliances under their control. The results show much greater impact on demand; for example Faruqi and Sergici (2010:216) found variation in the range 21%-32% was achieved. However, attracting a substantial proportion of demand into intervals during the day when the price was low had the effect of creating new demand peaks. This could not deliver the smoothing capability required and also as shown by Roscoe and Ault (2010:379) can have the effect of inducing oscillation in electricity market prices.

In effect the feedback provided by a dynamic price signal introduces new forms of complex system behaviour and seems unlikely to be able to deliver the functionality required. This behaviour arises from the non-linear response to the signal by the smart home device and also the consumers. So our goal was to find a way to make the response linear enough to provide controllability and stability without constraining consumers. One element of a suitable scheme must be energy storage to decouple supply and demand - in fact a simple way to solve the entire problem would be to provide sufficient storage between supply and demand so that the variability of both is absorbed. Using the established large scale solution this is impractical – if all the mountain valleys in the UK suitable for pumped storage of electricity were flooded for the purpose it would only provide 25% of the capacity needed (MacKay 2009: 194). However, traditional UK building construction in brick, stone and concrete results in high mass which can be used to store some thermal energy, as can the hot water tanks found in about 50% of homes. Electric vehicles also bring with them their own batteries that can be exploited. These adventitious stores combined with a realistic level of user tolerance in the operation of their appliances and a suitable control and signalling scheme can provide a useful level of demand flexibility.

In our proposed scheme linearisation at the level of aggregate demand is achieved using this flexibility without constraining the non-linear behaviour of individual consumers, as follows:

- The signal sent by electricity suppliers to consumers is a daily 48-value vector \mathbf{S} that is not inherently a tariff, but structured so that high values deter, and low values attract, electricity use in each half hour timeslot of the next 24 hours. The length of 48 is employed because the electricity market conventionally operates in half-hour timeslots.
- A “smart” control unit in the home or office responds to this signal by scheduling demand within a time window that meets user’s needs but in proportion to the attractiveness of the signal in each timeslot. The user needs are either determined automatically (such as the

amount of heat needed to achieve a comfortable room temperature) or are entered by the user (such as the time window within which the dishwasher must run).

- Minimisation of cost with respect to wholesale prices is performed by the electricity supplier who sets the shape of \mathbf{S} to meet their business needs and regulatory constraints.

To illustrate the operation of the smart controller, for electric space heating it introduces gaps in heating that occur in the less attractive timeslots with a probability proportional to the unattractiveness of the timeslot. These gaps are controlled in their duration and make use of the thermal mass of the building so that the user's comfort is not impaired. Refrigeration appliances are similarly "gapped" such that their cooling function is not impaired. In the case of water heating, this is performed in one or two of the more attractive timeslots with a probability proportional to the attractiveness, taking into account any cooling losses between the heating time and the user's habitual time for a shower. Wet appliances also run in timeslots selected randomly within the user's acceptable time but with an attractiveness bias. For vehicle charging, the charge in each timeslot within the user's acceptable time window is proportional to the attractiveness.

The effect of a proportionally biased random response to the attractiveness of the signal, when aggregated across a population of consumers equipped with a control unit having this behaviour, is to ensure that at least part of the aggregate demand \mathbf{D} has an approximately linear relationship with the signal \mathbf{S} . This relationship can be described by equations for each of the $i=1:48$ half hour timeslots in each day with the form:

$$D_i = B_i(1 + S_i k_i) + c_i$$

where \mathbf{B} is the baseline demand in the absence of any signal. The values of k_i and c_i vary for each timeslot because of the different types of appliance in operation and resulting level of demand in each half hour. They can be determined from the response to \mathbf{S} and potentially provide a model which the supplier can use to predict demand and shape it within limits determined by the baseline demand and the constraints applied by consumers. A more comprehensive mathematical description of this scheme is given in Boait *et al.* (2013).

Modelling Methodology

An agent-based model has been constructed to evaluate this concept (and others relating to the smart grid) using the Repast toolkit and framework developed by North *et al.* (2005). For this simulation there are 1000 agents each representing a household comprising a dwelling, occupants, a set of electricity consuming appliances and a smart control unit that executes the probabilistic algorithm described above when managing the appliances under its control. A single agent represents the retail electricity supplier who holds contracts with these households and is able to send them the signal \mathbf{S} each day. The attributes of each household, such as the number of occupants, the size of dwelling and usage pattern of electric vehicles are taken from distributions corresponding to UK national statistics. These attributes and their sources are summarised in Tables 1-3. In the absence of a signal, the operating cycle of each appliance is determined stochastically to model the individual decisions of the occupants such that in aggregate the total electricity consumption of that class of appliance corresponds with observed data both in magnitude and its distribution over 24 hours. This is the default daily profile indicated in Table 2.

Table 1*Household properties*

Attribute	Values	Notes
Occupancy	Between 1 and 6 with a mean of 2.4	Distributed according to national statistics for 2010 (ONS, 2013)
Hot water use	46+26n litres per day where n is occupancy	Energy Saving Trust usage model for UK households (EST,2013)
Thermal loss rate of dwelling	Distributed between 0.05 and 0.4 kW/°C with a mean of 0.225	Consistent with national building energy ratings (DCLG, 2012) and energy use (DECC, 2013)
Thermal mass of dwelling	Distributed between 5 and 20 kWh/°C with a mean of 12.5	Consistent with thermal loss rates and conventional UK construction

Table 2*Domestic appliance electricity use*

Appliance type	Default daily profile	Average demand (kWh/day)	Notes
Cold (fridge, freezer)	Flat	1.48	Average given total UK consumption in 2010 of 14TWh (DECC, 2013)
Wet (washing machine, dishwasher)	Simulated aggregate profile	1.52	Average given total UK consumption in 2010 of 14.4 TWh (DECC, 2013)
Heat pump (providing hot water)	Average hot water use profile	4.4	Profile from EST study (EST,2013)
Heat pump (providing space heating)	Determined by external temperature	29.5	Typical weather data for Birmingham, UK, from CIBSE (2013)
Non-controllable (cooking, lighting, entertainment, computers)	Simulated aggregate profile	5.82	Average given total UK consumption in 2010 of 55 TWh (DECC, 2013)

Table 3*Electric vehicles*

Attribute	Values	Notes
Vehicle population	A single car in 25% of households, of which 50% are battery-only, 50% plug-in hybrid	Based on 75% of households with a car (DfT, 2013) and 28% of cars are EVs
Battery capacity	24kWh for battery only EV, 16kWh for plug-in hybrid	Manufacturers' specifications for Nissan Leaf (Nissan,2013), and Vauxhall Ampera (General Motors, 2013)
Energy consumption	0.17 kWh/km (battery-only), 0.2 kWh/km (plug-in hybrid)	From manufacturers' running cost specifications
Frequency of use	0.74 journeys/day, return time distributed as indicated in Fig.1	Derived from National Transport Survey 2010 (DfT, 2013)
Journey distance	Average 27km, Poisson distributed between minimum of 4 and maximum bounded by battery capacity.	Weekday modelled, distance from DfT (2013)
Recharge time	Distributed between the minimum possible time and 07:00 next day	Models the expectation for recharge time applied by the user

When a signal S is transmitted by the electricity supplier agent, the control unit simulated within each household agent executes the proportionately biased random selection of running times (or not running times) of appliances as described above. In order to compare this mode of operation with the conventional cost-minimising objective function that has been employed to date in practical trials, the simulated control unit is also capable of treating the signal as a price and seeking to minimise cost for the consumer given their available flexibility in electricity consumption. In both modes the simulation assumes that the signal is presented to the occupants in the form of a price, so they are aware of those times of the day when electricity is more or less costly. The resulting limited price elasticity found in trials of about 5% is then modelled for non-controlled appliances, such as lighting and entertainment devices, to simulate occupants switching them on or off in response to the price. When the control unit is in proportionate mode, this occupant behaviour contributes to the k factor for each timeslot calculated by the retail electricity supplier.

Results

The simulation commences with an interval of a few days in which a null signal is provided to the household agents so that their baseline behaviour is obtained. Figure 1 shows the resulting

electricity consumption over 24 hours, on a cold winter day with overnight temperatures falling to -1.4 °C. The same weather conditions and population of 1000 households are employed for all the results shown.

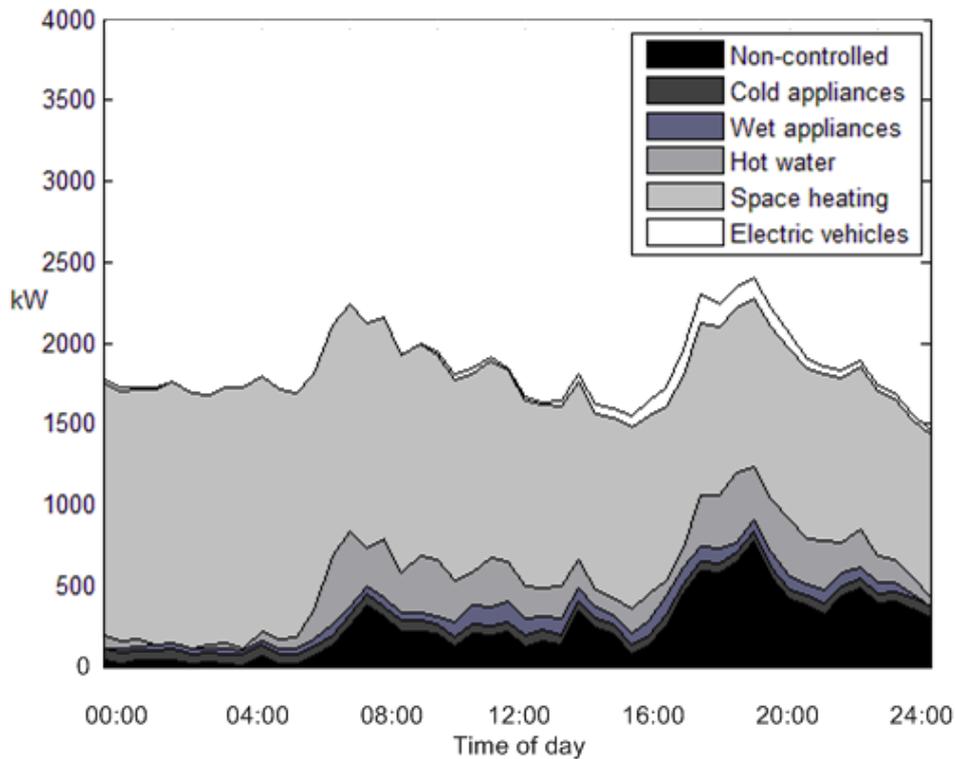


Figure 1. *Baseline winter demand for 1000 households from agent-based model*

Then with the control units in proportionate mode a training sequence of values for S is transmitted over several days by the simulated retail electricity supply agent allowing it to learn the linear response characteristics of its customers. Finally the electricity supplier agent uses this learned model of customer response to construct and send a signal optimised to elicit a particular desired response depending on the scenario and the result is captured. Figure 2 illustrates the training response for a single i th timeslot by plotting $S_i B_i$ on the x-axis and the resulting δB_i on the y-axis for different values of S_i . The slopes of the regression lines either side of the y-axis and their y-axis intercepts provide k_i and c_i values for positive and negative values of S . The scatter of points reflects the stochastic nature of the demand response as the attraction offered by S_i varies.

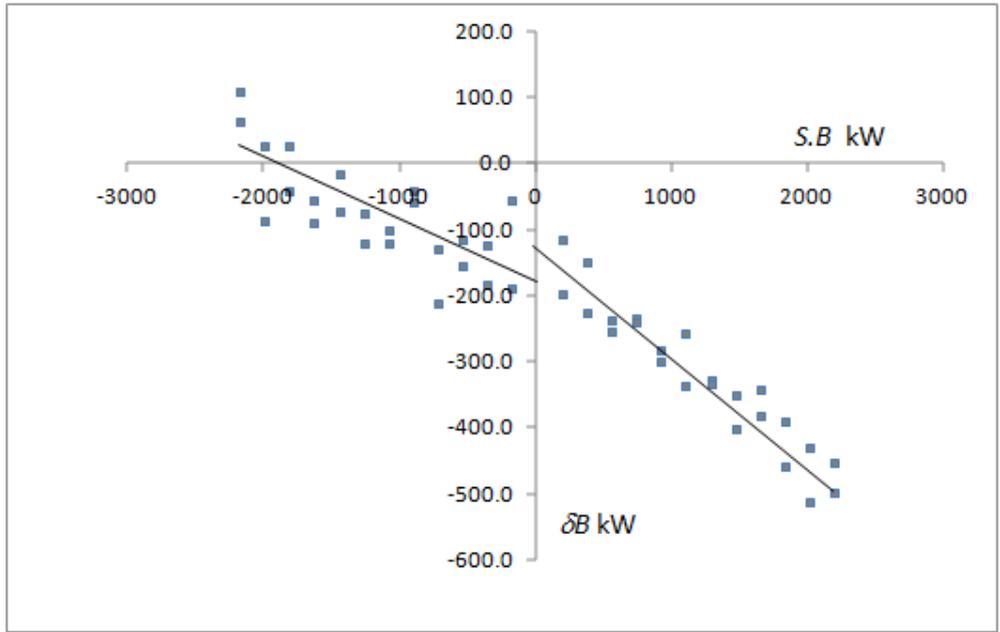


Figure 2. Linear response of aggregate demand to S with proportionate control

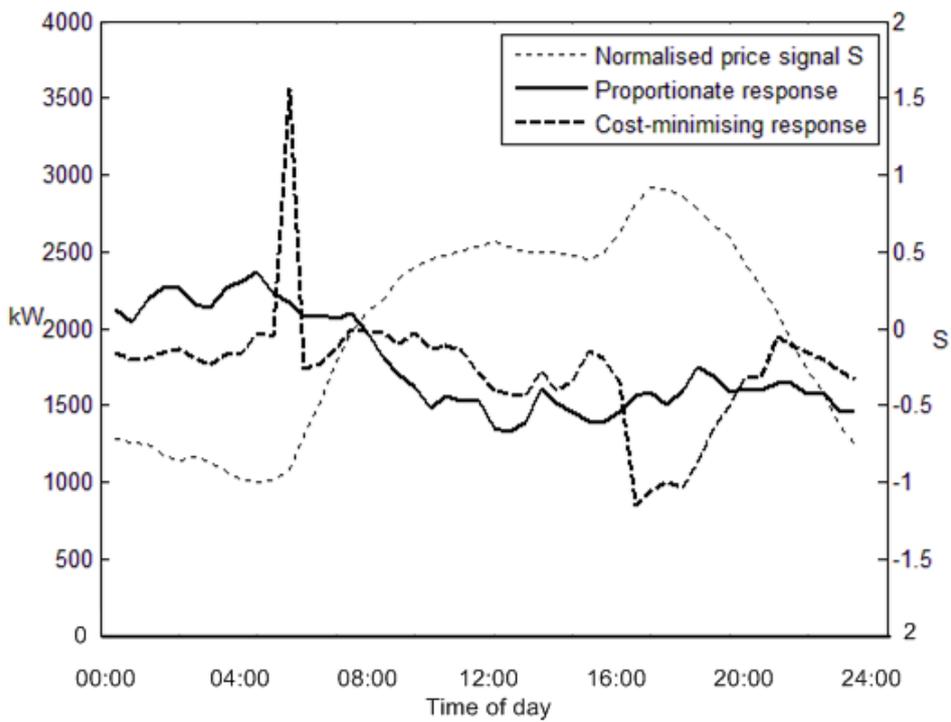


Figure 3. Comparison of proportionate and cost-minimising control algorithms

In Figure 3 a comparison is provided of the total demand profiles resulting from proportionate and cost-minimising responses in the control unit when the population is presented with a signal that follows the shape of the national aggregate demand on a winter day. Since electricity market prices tend to track demand this is a reasonable proxy for an actual price profile. The peak in demand at the cost minimum illustrates the expected non-linear response of a cost driven scheme. Obviously if

this response was a significant proportion of the national demand this spike would feed back into price setting in subsequent days with path dependent consequences that would not be helpful to maintenance of system equilibrium. By contrast the proportionate response has less variation than the signal so has an inherent damping effect that should assist system stability.

The full ability of the proportionate control scheme to flatten demand is shown in Figure 4, where the supplier agent uses the model of household demand response obtained during training to calculate a signal that is optimised to produce a response with minimum deviation from the mean. Alternatively a retail electricity supplier might choose to send a signal that is optimised to make use of an overnight surge in wind generation as shown in Figure 5. The scope for shaping demand using this method and scenario is shown in Figure 6 in the form of upper and lower limits. It can be seen that the available flexibility as a proportion of baseline demand varies from 43% at 00:00 to 13% at 24:00. This falling flexibility is partly a consequence of the fact that an essential demand arising from a user need that must be satisfied by a given time can only be made to happen earlier. It is also an artefact of an assumption that the signal is transmitted at midnight for the following day and responses to that signal can only take place within the day. A more complex scheme allowing a rolling update to the signal would allow needs such as hot water for morning showers to be met using electricity drawn the previous evening hence reducing the discontinuity at midnight.

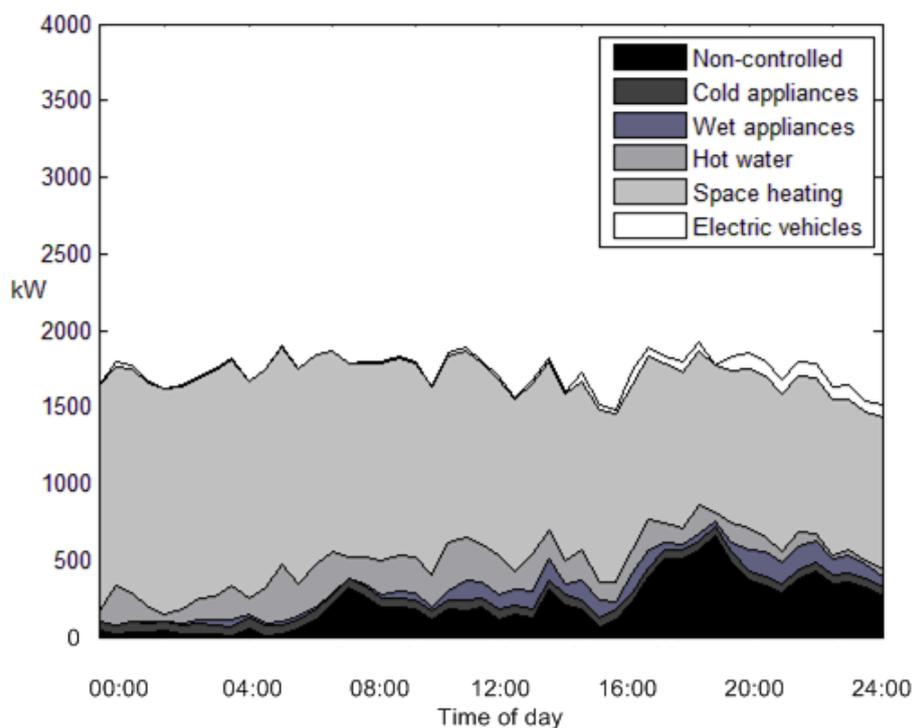


Figure 4. Demand response to a signal optimised for flattening

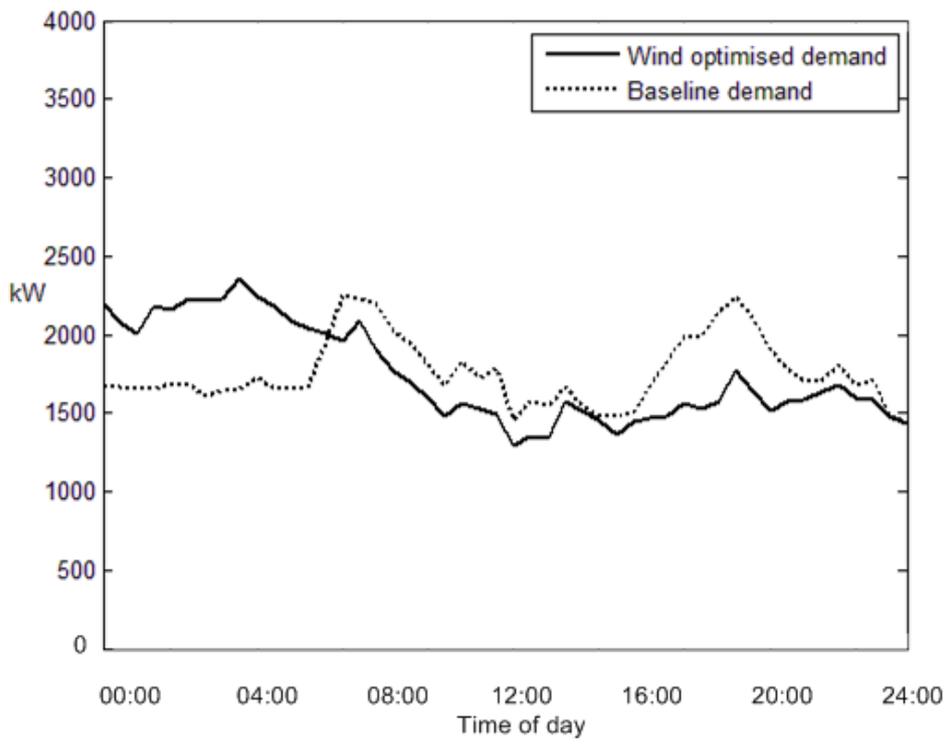


Figure 5. Demand response optimised to exploit overnight availability of wind generated electricity

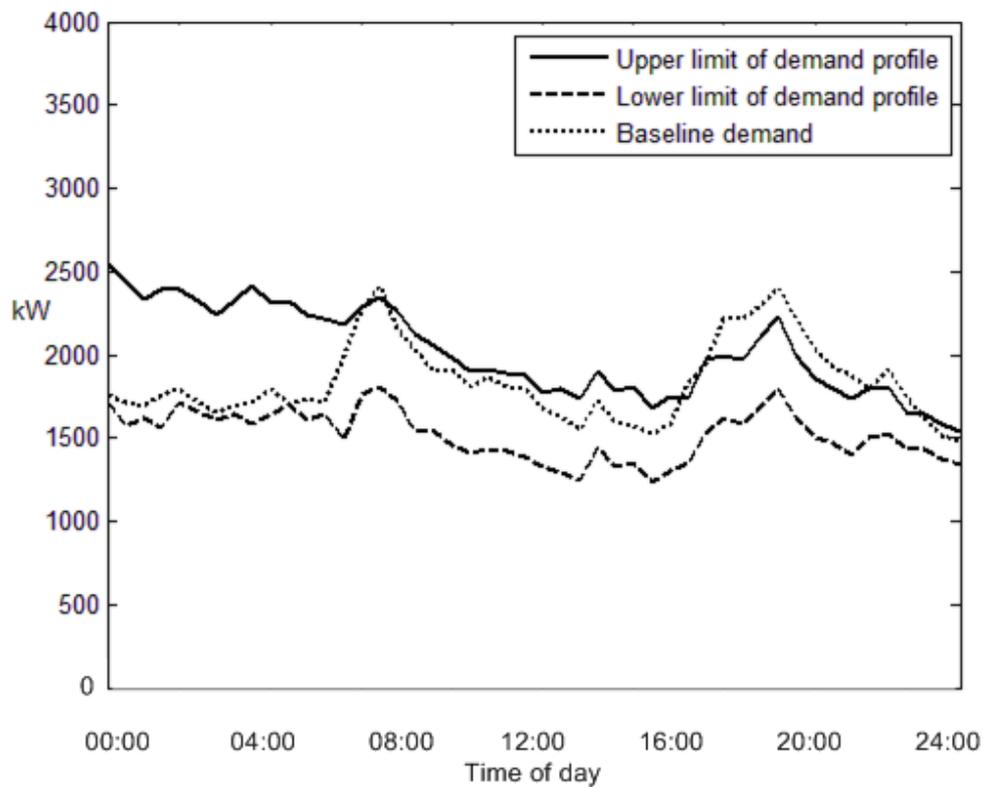


Figure 6. *Upper and lower limits to demand response from proportionate control*

Discussion and summary

In this agent-based modelling experiment we have demonstrated how it should be possible to use a distributed “smart home” technology to introduce a degree of imperfect linearity into the otherwise complex patterns of domestic electricity consumption. This somewhat linear response to a signal from the electricity supplier is sufficient to allow the flexibility in electricity consumption afforded by consumer behaviour and the energy storage properties of buildings, heating systems and electric cars to contribute to the dynamic stabilisation of the grid. It also illustrates how a complexity perspective can expose possible solutions to a system scale problem that cannot be solved with price structures and rational economics alone.

In order to apply this capability to the two challenges outlined in the Introduction, of flattening demand on distribution networks and responding to variability of weather-dependent renewable electricity generation, an additional organisational issue must be confronted. In the UK as in other countries with a competitive electricity market, regional distribution networks are owned by companies that are regulated monopolies. These must operate at arm’s length from retail electricity suppliers who compete to hold the relationship with the consumer. So a distribution network operator concerned about the loading on a cable in a single street must interact with the relevant households via several retail suppliers. Also, to preserve consumer and commercial confidentiality, the metering data for a single household cannot be shared with the network operator, who must manage with aggregated data for each network segment. Meanwhile some of the suppliers with customers on the street may wish to exploit a surge in wind generation as shown in Figure 5 by boosting the demand from their customers at the relevant time of day.

From this investigation we are able to outline a process by which these competing interests might be reconciled. The network operator is faced with physical limits for the power that can be carried by its network assets so these must take priority over efficient use of renewable generation. So the network operator notifies all the suppliers with customers on our example street (and every other street on the network) of a maximum power limit for each household. This limit might be profiled during the day, for example if there were industrial premises on the street that did not operate out of working hours then a higher limit might be available to domestic consumers in the evening and overnight while the industrial consumers would be given lower limits. The limit would of course have to be determined equitably using rules set by the electricity market regulator. The supplier compares the limit for each consumer with their historic metering data and assesses the risk of that consumer exceeding the limit. Depending on the risk, each consumer is assigned to a group that will receive a particular signal. A consumer with little headroom, either because of their heavy consumption or because they are on a constrained network segment, would be sent a flattening signal with results as shown in Figure 4. A consumer with low electricity use or a network connection with ample capacity could be sent a signal that shaped demand according to the electricity supplier's preferred outcome as shown in Figure 5. Consumers with intermediate characteristics could be assigned to intermediate groups, it is envisaged that only a few would be needed. This simple categorisation allows the process to be manageable at the scale of the millions of customers held by each supplier and will result in groups that are big enough for their linear properties in aggregate to emerge.

To ensure the network operator's limits were respected, the supplier would be obliged to operate a regulated audit process that would identify from metering data those consumers who exceed their profile and give the network operator statistics for such occurrences. The stochastic nature of the response to the signal S means that a certain incidence of profile exceptions will inevitably occur. Where the level is excessive then the supplier would have to review their consumer categorisation and signalling policy. In a situation where the demand was being flattened as far as possible through induced response and the profile limits were still being exceeded, then that would be evidence which the network operator could present to the regulator to justify network reinforcement or imposition of a physical tripping limit on consumption.

Testing this concept requires a further elaboration of the agent-based model that is work in progress, to include a physical representation of distribution network elements and the network operator agent, and also a simulation of the electricity market so that the commercial pressures and associated learning processes of the retail supplier agents are brought into play. This will be a realisation of one of the "new tools" identified by Elliott (2010:14) as necessary for analysis and design of sustainable energy systems.

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