FORECASTING THE IMPACTS OF THE ELECTRIFICATION OF HEAT, COOLING AND MOBILITY IN FUTURE NET ZERO URBAN AREAS

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ABSTRACT

The electrification of heat, increased demand for cooling in buildings and the charging of electric vehicles by commuters as the UK transitions to net zero, poses a significant challenge for urban electricity networks. Growth in peak electrical demand could result in the need for substantial investment in infrastructure, ultimately leading to costs for consumers. Conversely, there are many measures that could mitigate demand growth including improved building fabric efficiency, load management and local generation from PV. Using a case study of Glasgow City Centre, a modelling approach which uses minimal stock data along with a combination of building simulation, existing building archetypes, an EV charging model and a custom urban energy system modelling tool is used to predict peak demand changes for secondary substations for a set of future energy scenarios. The results indicate that, for most of the secondary substations modelled, the impacts of the electrification of heating and transport can be offset or reversed by building efficiency improvements and load management, with most substations showing only a modest increase in demand or a demand decrease. However, for those substations where EV charging demand dominated, peak demand increased substantially.

Keywords: substation, building simulation, demand, scenarios, EV, electrification of heat.

INTRODUCTION

The UK has committed itself to decarbonisation by 2050 (UK Government, 2019). Consequently, radical changes in its energy supplies and in use of energy will be required, particularly in the built environment, which is the UK economy's second largest single energy consumer, accounting for some 30% of total final energy consumption (DESNZ, 2023) and 59% of electricity consumption (Committee on Climate Change, 2020). Decarbonisation will radically alter the characteristics of urban demand, possibly resulting in large increases in electrical energy use and in electrical peak demands (e.g. McGarry et al, 2024). These changes could be most significant in city centres, where building and population densities are at their highest, and where measures such as the decarbonisation of heat and transport, and increased cooling have their greatest impact on energy networks. Urban Energy modelling can assist in signposting likely changes in demand, providing the data needed to assist energy systems planners and policy makers make key decisions on the trajectory of the energy system.

REVIEW

Urban energy modelling is a developing field, with modelling approaches tending to fall into two main camps, so-called "bottom-up" and "top down" modelling (Swan and Ugursal, 2009). This paper focuses on bottom-up tools that utilise building-level, detailed modelling output, which is then scaled-up. By contrast top-down tools use high-level energy demand data. Bottom-up energy models typically rely on building stock archetypes, using building energy modelling (BEM) tools such as EnergyPlus (Crawley *et al*, 2001) to generate performance data, that can then be extrapolated to the urban and even national scale using a variety of city modelling platforms (Abbasabadi & Ashayeri, *ibid*). Bottom-up models offer the analytical flexibility needed to quantify the impact of *specific* changes to buildings and system, that can then be extrapolated to the larger scale. But a challenge with this approach, is the need for substantial quantities of data with which to populate models. The modelling approaches of Steemers (2003), Prataviera et al (2021) amongst others, rely on significant amounts of building data. However, specific information on building fabric, materials occupancy, energy systems and their control is rarely available and could be prohibitively expensive to gather at scale.

AIMS

In this paper, an archetype-based "bottom-up" modelling tool, which relies on very limited amounts of building data, was used to predict future peak electrical demands for Glasgow substations under a variety of possible urban decarbonisation scenarios.

METHOD

The modelling approach behind the tool makes use of limited, but readily available information: total building floor area and building type connected to a substation (SPEN, 2019). Six basic building type ESP-r[1] (Clarke, 2001) models, that correspond to those identified as connected to the urban substation network in the SPEN dataset, were selected (and adapted where necessary) from previous projects. These were retail premises, offices, hotels, entertainment, hospitality and high-density housing (flats). The performance of each model was simulated over two characteristic climate weeks (summer and winter) to generate baseline, time-varying, building-specific energy demand profiles, which were disaggregated by load type and normalised by building floor area (Table 1).

Substation Demand Data Forecasting

Eighteen disaggregated baseline archetype demand profiles were created, comprising 2 x 6 x 1-week sets using a Glasgow test reference year climate data set, at half-hour time increments.

To generate a substation profile, the individual archetype building profiles were *scaled* → *diversified* → *transformed* (where appropriate) and finally → *combined*.

Table 1: profiles generated from each archetype.

	Profile	Profile type (all units kW/m²)
1	Space heating load	Thermal
2	Space cooling load	Thermal
3	Hot water load	Thermal
4	Lighting	Electrical
5	Lifts and HVAC	Electrical
6	Appliances	Electrical

Scaling – each base profile was scaled based on the total occupied and serviced floor area[2] of each archetype connected to a substation (SPEN, *ibid*). So, for any building type *i* with a load *j*, the scaled demand (W) at some time *t*, $D_{i,j}(t)$, was given by:

$$D_{i,j}\,(t) = D_{i,j-b}\,(t) \times A_i \times f_{a,i} \times\, f_{o,i} \qquad (1)$$

$D_{i,j-b}(t)$ is the normalised demand in the base profile (W/m²), A_i is the connected floor area (W), $f_{a,i}$ is the treated floor area fraction and $f_{o,i}$ is the occupancy rate for building type i.

Diversification - each scaled profile was subdivided into a maximum of 20 1kW blocks, which were then shifted backwards or forwards in time randomly, based on a normal time-shift distribution around a mean of 0 hours (μ = 0); the standard deviation was $\sigma = 0.6$, which was derived iteratively from a qualitative comparison with monitored data.

$$\boldsymbol{D}_{i,j,k} = \frac{\boldsymbol{D}_{i,j}}{N} = \begin{Bmatrix} D_{i,j,k}(0), D_{i,j,k}(0.5), \dots, \\ D_{i,j,k}(168) \end{Bmatrix} \qquad (2)$$

[1] ESP-r computes the energy and environmental performance of the building and its energy systems over a user-defined time interval (e.g a day, week, year), explicitly calculating all the energy and mass transfer processes underpinning building performance.

[2] It was assumed that 0.85 of the connected floor area was actively serviced (i.e. contributed to energy use) and that there was a 85% occupancy rate for offices and 80% rate for retail premises in the city centre, such information is typically available from property agency surveys e.g. Savilles, 2023, SFN, 2023.

$$\boldsymbol{D'}_{i,j,k} = \begin{Bmatrix} D_{i,j,k}(0+R_k), D_{i,j,k}(0.5+R_k), \dots, \\ D_{i,j,k}(168+R_k) \end{Bmatrix} \quad (3)$$

$$\boldsymbol{D''}_{i,j} = \left\{ \sum_{k=1}^{k=N} \mathrm{D}_{i,j,k}(t') \right\} \quad (4)$$

$$t' = t + R_k \in (0.5, 1, \dots, 167.5, 168)$$

$\boldsymbol{D}_{i,j}$ is the original electrical demand profile vector for building type i, load type j; N is the number of subdivisions, $\boldsymbol{D'}_{i,j,k}$ is sub vector of $\boldsymbol{D}_{i,j}$ and $k \in \{1 \dots N\}$. R_k is the random time-shift for subdivision k. Here, $\boldsymbol{D''}_{i,j}$ is the reconstituted, diversified profile. Note that:

$$t + R > 168 \longrightarrow t = t + R - 168 \quad (5)$$

$$t + R < 0 \longrightarrow t = 168 + R \quad (6)$$

Transformation – heating or cooling demands met using a heat pump or chiller could be transformed to and equivalent electrical demand profile using:

$$D'''_{i,j}(t) = f_{HC} \frac{D''_{i,j}(t)}{COP} \quad (7)$$

$D'''_{i,j}(t)$ is the electrical demand associated with heating or cooling; $D''_{i,j}(t)$ is the post-diversity heating or cooling demand and COP is the coefficient of performance of the heating or cooling device; f_{HC} is the fraction of the heating or demand serviced by heat pumps or fraction of buildings with cooling capability.

Combination - the final substation load is the summation of each scaled and diversified archetype building type electrical demand profile, along with the supplementary PV generation and EV demand profiles; these were generated using pre-existing high-resolution models (Kelly *et al*, 2023). The PV was assumed to be roof mounted and inclined at the optimum of 30° for Glasgow.

So, the load at the substation at some time t would be:

$$D_{sub}(t) = \sum_{i=1}^{i=\mathrm{o}} \sum_{j=1}^{j=\mathrm{p}} D'''_{i,j}(t) + D_{EV}(t) + P_{PV}(t) \quad (8)$$

Where o is the number of building types connected to a substation and p are the number of distinct building electrical load types (e.g. lighting, heating, EV charging, etc.). Note, not all loads required to be transformed using all steps. So, for an electrical load, which only requires scaling and diversification such as a lighting load, $\boldsymbol{D'''}_{i,j} \equiv \boldsymbol{D''}_{i,j}$. Figure 1 illustrates the profile generation approach for an archetype.

BASELINE COMPARISON

To assess the veracity of the approach, measured demand data (from 2019) was available for six Glasgow city centre substations (Substations A-F) shown in Table 1. Substations A, B and E mainly serve office space. Substations D and F mainly serve retail space and substation C serves a mixture of building types. The data from each substation data was processed to generate demand profiles for a winter, transition and summer week. Corresponding substation demand profiles were then generated (blind) using the approach outlined previously, based only on estimates of the floor area of each building archetype connected to a particular substation (SPEN 2019).

Table 2 summarises the comparison. The mean difference between modelled and measured data varies significantly from substation to substation, with a mean absolute error of 21%. The error in predicted peak demand[3] again varies, with a mean value of 12%. The mean error in minimum demand was 39%. The mean Pearson correlation was 0.9 The errors in the table include both over and under estimation of demand: positive and negative values, respectively. So, with minimal input data, the approach is relatively successful at predicting peak demand and approximating the shape of the electrical demand profile, less so at minimum demand. To put these differences in context, the discrepancies here are well within the range of

[3] Peak and minimum values are the 99th percentile and 1st percentile values, respectively, to reduce the impact of outlying values.

values reported by van Dronkelaar et al (2016) for well-characterised non-domestic buildings.

Figure 1 illustrates a good fit and weaker fit respectively from the results. This comparison indicates that, with very limited data input, the modelling approach can produce a reasonable proxy of the electrical demand seen at urban substations; however, the limitations of the approach were also clear in that demand characteristics, not captured in the underpinning archetype model, leads to significant discrepancies between the simulated and modelled data.

MODELLING FUTURE DEMAND

Accepting the caveats on accuracy, the approach (encapsulated in a custom modelling tool) was used to assess possible, future changes to substation electrical loads in Glasgow City centre, which is dominated by retail and office buildings, with some high-density housing and entertainment venues. This future demand assessment was based on five scenarios – the baseline case and four 2050 UK National Grid scenarios (FES, 2023):

- *falling short*: “failure to reach 2050 targets, slow progress on decarbonisation, reliance on natural gas, slow uptake of EVs.”
- *system transformation*: “2050 targets met by supply side changes, hydrogen heating with limited energy efficiency improvements, combination of EVs and fuel cell vehicles; hydrogen from natural gas with CCUD.”
- *Consumer transformation*: “2050 targets met by consumer-side changes. Heat from heat pumps, extensive energy efficiency improvements, widespread use of EVs and demand side management.”
- *leading the way*: “2050 target met early, high level of energy efficiency improvements with extensive smart energy services.”

The translation of these scenarios into inputs for the profile generation tool is shown in Table 4.

Glasgow city centre is served by over 200 secondary substations, connected floor area data for these was made available by SPEN (2019); an example of the data is shown in Table 2. To keep the modelling and data analysis task for this paper manageable, a subset of 10 substations was selected, these were chosen to represent the diversity of load types connected to the urban substations: those with a) near average floor areas of each archetype building and b) those with higher than average concentrations of specific building archetypes, e.g. substations with a predominance of retail premises, substations with a predominance of office premises, etc. and c) substations with less than average floor area of buildings attached. For reasons of data confidentiality, the names of substations have been anonymised.

For each of the base case and future demand scenarios, an electrical demand profile was generated for each substation, for a typical winter and summer week.

RESULTS AND DISCUSSION

Figure 2 shows an example of the time series output from the modelling tool, showing the change in winter and summer demand over a 48-hour period for all scenarios. This time series data was refined to generate information on substation peak demand.

The key parameter assessed for each scenario and for each substation in the sample was the peak demand; this is used by UK utilities to assess whether an asset such as a substation needs to be upgraded or replaced. The percentage change in peak demand (Δ_{PD}) relative to the base case was quantified for each scenario as follows.

$$\Delta_{PD} = 100 \times \frac{\widehat{D_s} - \widehat{D_b}}{\widehat{D_b}} \qquad (9)$$

Where $\widehat{D_s}$ is the peak demand occurring in the scenario, and $\widehat{D_b}$ is the peak demand seen in the baseline scenario.

Figures 4 and 5 illustrate that the impact of the different scenarios is a complex one, with increases and decreases in the level of peak demand evident in both summer and winter and for all scenarios. The following paragraph summarise the results emerging for each scenario.

Falling Short – most substations showed an increase in winter peak demand; those substations with a small floor area of connected buildings show a significant increase in demand relative to the baseline, due to EVs charging. Substations with significant floor areas of office space attached to them see a modest drop in demand; here, reduced building heating through modest improvements in energy efficiency outweigh any increase in peak demand due to EV charging and limited heat pump uptake. Median peak demand change from the baseline was +6%. In summer (Figure 7) many substations show a decrease in peak demand due to PV generation and modest improvements in energy efficiency. Again, substations showing an increase in load due to EV charging had few buildings connected to them. Median peak demand change was -3%

System Transformation – Most substations showed a decrease in winter peak demand, due to use of hydrogen heating and district heating. Only substations with a substantial EV charging demand show an increase in peak demand. Median peak demand change was -3%. In summer most substations show a decrease in peak demand as modest levels of PV and appliance efficiency improvements offset increased cooling demand and EV use. Median peak demand change was -10%.

Consumer Transformation – the picture was mixed for this scenario, where there was high uptake of EVs and heat pumps. In winter most substations showed increased demand due to EV charging and heat pump use. Improved efficiency and load control were not enough to offset this. The median increase in peak demand was +6%. In summer, demand typically reduced, as this scenario included substantial quantities of rooftop PV, in most cases this offset increased demand due to EV charging and cooling. The median peak demand change was -22%.

Leading the Way – this scenario resulted in most substations showing a decrease in demand in winter, as improved fabric efficiency, lighting control, and load shifting offset the impact of increased heat pump use and EV charging. The median change in winter demand was -12%. In summer, other than those substations dominated by EV charging, peak demand was reduced, due to local PV generation, improved fabric efficiency and lighting control. The median change in peak demand was -22%.

CONCLUSIONS

The future demand for a subset of Glasgow substations was modelled for a baseline case and four future electricity FES scenarios: falling short, system transformation, consumer transformation and leading the way. These scenarios allowed combinations of future changes to be assessed.

Significant increases in peak demand were seen at substations serving few buildings; here, the addition of EV charging to a small existing load led to a significant increase in peak demand.

In substations with substantial connected floor areas, the impact of EV charging was far less[4] significant, and the increase in demands compared to the baseline scenario was modest, with energy efficiency measures, improved control of lighting, load shifting and PV generation largely offsetting increased use of electricity for heating, cooling and vehicle charging.

Demand was on average slightly higher in future scenarios winter than in the baseline scenario, due to increased electrified heating (particularly heat pumps). Glasgow city centre already has a substantial number of electrically heated non-domestic buildings, and so a shift towards to heat pumps only had a limited effect.

Summer demand was generally lower than the baseline scenario in the more progressive future scenarios due to rooftop PV offsetting some the peak daytime cooling load. In some rare instances, the PV generation wholly offset or exceeded the demand.

Overall, with the exception of those substations where EV demand was dominant, the impact of

[4] Note that the EV charging modelled here only accounts for public charging, not home charging.

urban electrification was relatively benign, with growth in peak demand in the more ambitious scenarios seen to be offset by improved energy efficiency, better control of loads and local electrical generation from PV.

Finally, this study considered mainly non-domestic premises in the Glasgow city centre, it does not include a significant domestic element, consequently the impact of home charging (as opposed to use of public charge points) and electrified domestic heating was not assessed.

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Table 2: Baseline calibration substation details, connected floor space (m^2) and type (SPEN, 2019)

	Retail	Hotel	Hospitality	Entertainment	Office	Domestic
Substation A	-	-	-	-	7,111	-
Substation B	-	-	-	-	13,172	-
Substation C	164	4,838	-	97	14,419	80
Substation D	10,834	0	1,366	1,636	2,251	80
Substation E	-	-	-	-	9256	-
Substation F	11853	-	-	389	-	-
Total in dataset	28,189	82,854	59577	4858	1,017,231	33,120

Table 3: differences and correlation between modelled and measured substation profile data.

Substation	A winter	A transition	A summer	B winter	B transition	B summer	C winter	C transition	C summer
Mean error %	31.5	38.5	73.3	36.6	27.3	31.9	23.2	22.1	20.6
Correlation	0.8	0.9	0.9	0.7	0.9	0.9	0.9	0.9	0.9
Max demand error%	0.9	3.8	78.0	4.9	3.6	17.3	7.5	16.6	6.3
Min demand error %	40.5	18.8	2.2	31.4	21.7	15.3	43.4	47.0	42.9
Substation	D winter	D transition	D summer	E winter	E transition	E summer	F winter	F transition	F summer
Mean error %	18.7	13.1	13.3	25.9	21.9	23.3	35.2	28.9	34.4
Correlation	0.9	0.9	0.9	0.9	0.9	0.9	0.5	0.8	0.8
Max demand error%	3.7	4.2	2.5	13.4	3.5	11.6	10.5	13.7	12.4
Min demand error %	9.1	7.3	14.6	43.0	42.5	45.8	65.3	97.0	106.5

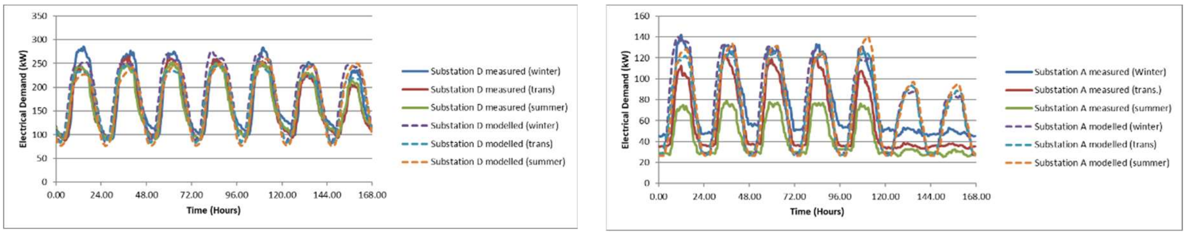

Figure 1: good and weaker fit to measured data.

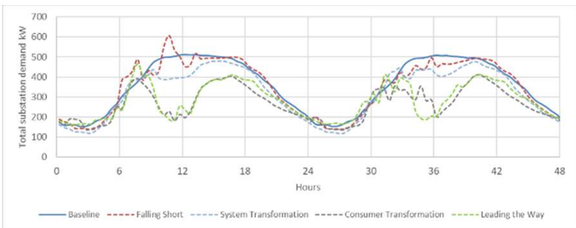

Figure 2: example output showing changing winter demand with scenarios (substation with mix of building types).

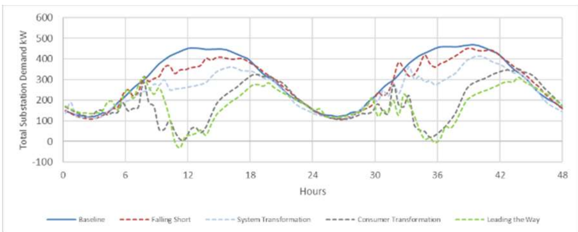

Figure 3: example output showing changing summer demand with scenarios (substation with mix of building types).

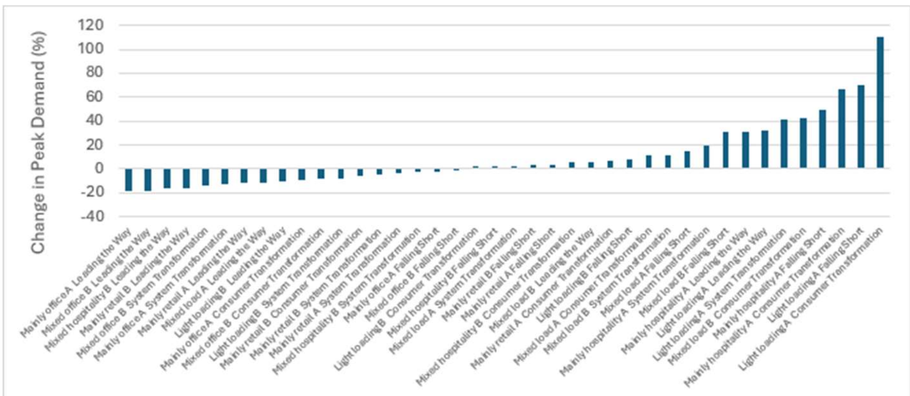

Figure 4: Change in peak winter demand for all substations and scenarios.

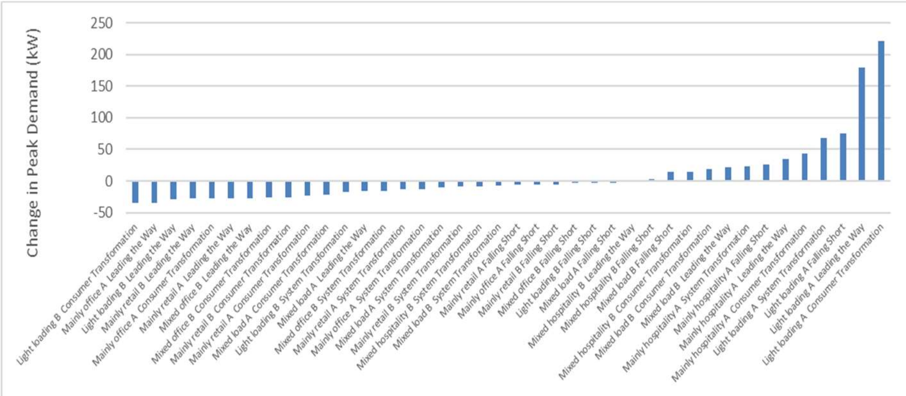

Figure 5: Change in peak summer demand for all substations and scenarios.

Table 4: details of baseline (2019) and future scenario data inputs.

		2050 Decarbonisation Scenarios			
	Baseline Model	Leading the Way	System Transformation	Consumer Transformation	Falling Short
Electric heating	50% of commercial premises are heated electrically, direct electric in smaller premises and heat pumps/air conditioning in larger premises. 30% of housing is heated electrically. (Scottish Government, 2018)	Significant investment in heat pumps and low carbon district heat. Replacement of all gas heating. 60% of space and water heating by heat pump. 20% direct electric, 20% district heat.	Continued reliance on combustion heating. 60% of space heating H_2, 20% direct electric, 20% heat pump.	Heat pumps commonplace, 70% of space heating from heat pumps, 10% from low-carbon district heating, 20% from direct electric.	Slower uptake of heat pumps. 40% of demand met by heat pumps with 20% from direct electric and remainder from gas.
Electric cooling	Around 30% of the floor area connected to city centre substations is actively cooled. Scottish Government (2018).	Limited growth in cooling due to energy efficiency drive. 35% of floor space is cooled.	Limited uptake of cooling technologies due to cost. 35% of floor space is cooled.	Some uptake due to increased expectations of comfort energy efficiency and high cost. 40% of floor space is cooled.	Higher demand for air conditioning due to increased comfort expectations, rising temperatures and higher indoor gains. 40% of floor space is cooled.
Electric vehicles	Limited EV charging, EVs made up >5% of the vehicle population in 2019.	All vehicles are EVs by 2040. Up to 50 chargers in a substation area.	Mix of H_2 and EVs, up to 25 EV chargers per substation area.	EVs are ubiquitous. Up to 50 chargers per substation area.	Slow growth in EV uptake, 20 chargers per substation area.
Appliance demand	Appliance demand levels representative of UK existing buildings.	Appliance demand reduced due to energy efficiency drive. 35% reduction in appliance demand.	Demand remains fairly static, with limited investment in energy efficiency. 10% reduction in overall appliance demand.	Demand reduced due to preference for energy efficiency. 25% reduction in appliance demand.	High demands for consumer appliances, less focus on energy efficiency. 5% reduction in appliance demand.
Building fabric	The typical EPC rating of commercial buildings is category D. Model constructions reflect this (Scottish Government, 2018)	Tightening of building regulations towards zero-carbon new build. 50% of buildings significantly upgraded.	Limited investment in building fabric improvements only new build are improved. 25% of buildings upgraded.	Tightened building regulations and investment in retrofit. 60% of buildings upgraded.	Little investment or interest in demand reduction only improvements in new build. 15% of buildings upgraded.
Lighting control	Limited lighting control penetration was assumed (15%).	Significant use of lighting control due to drive towards energy efficiency and carbon reduction. 80% of lighting systems controlled.	Low uptake. 25% of lighting systems controlled.	LED lighting and lighting control popular demand reduction options. 60% of lighting systems controlled.	Less interest in energy efficiency, gradual uptake of LED and control. 15% of lighting systems controlled.
PV	Assumed negligible.	High investment in and PV. 10% of roof area PV.	Low uptake of new technologies continued reliance on existing systems. 5% of roof area PV.	Widespread uptake of microgeneration 10% of roof area PV.	Limited growth in PV, accounting for 3% of total roof area.
Load shifting	No load shifting.	Significant uptake of time of time of use tariffs and load shifting. 80% uptake of load shifting.	Consumers not engaged with load shifting. 5% uptake of load shifting.	Widespread uptake of load shifting 70% of end users implement load shifting.	Limited development in load shifting 10% uptake.