PREDICTING THE EFFECT OF CHANGES TO THE URBAN ENVIRONMENT ON FUTURE ELECTRICAL DEMAND USING BUILDING SIMULATION AND ARCHETYPE MODELS

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ABSTRACT

Future urban electrical loads are of interest to a range of stakeholders from utilities to network planners. In this paper, a pragmatic approach to the modelling of urban electrical demands using archetype models and simulated building demand profiles is described. The profiles can be scaled, transformed and combined to produce time-series electrical loads for multiple buildings connected to a substation in a distribution network. The modelling approach has been verified against measured demand data. Possible changes in future peak urban electrical demand were quantified for a sample of substations in Glasgow, UK, using four future demand scenarios. The picture emerging was complex, with peak demand increasing in some cases where electric vehicles and electrified heating combine. However, there were many situations where a combination of improved energy efficiency and microgeneration lead to reduced peak demand.

INTRODUCTION

With the UK committed to an 80% reduction in greenhouse gas emissions by 2050 (Committee on Climate Change, 2008), radical changes in the supply and demand of energy will be required. Nowhere will this be more necessary than in the built environment, which is by far the largest energy consumer in the UK economy (DECC, 2015). Such changes could include removing fossil fuels from the energy mix through the electrification of heat and transport; significant improvements in building energy efficiency; increasing use of renewable and low carbon microgeneration and the use of flexible demand to accommodate renewable energy supplied. Such changes could alter the characteristics of urban demand beyond recognition. These characteristics are of concern to UK energy utilities, network operators and regulators, as future energy supply systems will need to evolve to accommodate a radically changed operating environment (e.g. National Grid, 2015). At the urban scale, a range of key challenges could emerge in the near future including: electrified heating and increased cooling; charging of electric vehicles (e.g. Salah et al, 2016); 'tidal' electrical energy flows, with periods of high demand, set against periods of reverse power flow from PV or CHP (e.g. Cipcigan and Taylor, 2007; Kadurek et al. 2011).

These challenges will be most significant in city centre areas, where building and population densities are at their highest and where those factors outlined tending to increase demand will have their greatest impact on energy networks. Conversely, actions to mitigate electrical demand growth could also be most beneficial.

AIMS

This paper outlines a pragmatic modelling method (encapsulated in a tool) for the prediction of future urban electrical demands, which generates disaggregated electrical profiles for urban substations under a range of operating scenarios that can include the electrification of building heating and cooling, growth of microgeneration and the increased use of EVs amongst others. The tool was applied to the prediction of the future electrical demands in the city centre of Glasgow, UK. Substations were the focus of the work as these are key pinch points in the network (e.g. Salah et al, 2015), and the first asset that would need to be upgraded or replaced due to growth in electricity demand.

STATE-OF-THE ART

The area of urban energy modelling has been described as a nascent field (Reinhardt and Davila, 2016) with modelling resources tending to be concentrated in two areas: bottom-up tools using data derived from detailed modelling and top-down tools based on meta-data of energy demand.

Top-down models typically employ macroeconomic data and regression to make predictions of energy use at the large-scale (e.g. Lorimer, 2012), extrapolating from the present situation, and so are less suited to predicting the impact of future changes. Bottom-up energy models can make use of data derived from individual archetypes of the housing stock, using building simulation tools such as EnergyPlus (Crawley et al, 2001) or ESP-r (Clarke, 2001). This base data can then extrapolated to the urban and even national scale (Famuyibo et al, 2012). In the case of modelling of urban electrical demand, bottom up models offer the analytical flexibility needed to quantify the impact of specific changes to buildings and communities on demand.

A challenge faced when developing building-simulation-based bottom-up models is the need to gather detailed information on the buildings whose performance is to be simulated. Notable urban energy modelling efforts include Steemers (2003), Kampf and Robinson (2007) and latterly Tereci et al (2012) all rely on significant amounts of building geometric data. However, when modelling large numbers of real buildings, specific information on building fabric materials occupancy, energy systems and their control is rarely available and could be prohibitively expensive to gather. Approaches have been developed to gather geometric information on buildings from sources such as satellite images (e.g. Ghaffarian et al, 2014); however these approaches are embryonic and still subject to significant error and require appreciable human intervention to produce usable models (Haala and Kada, 2010).

METHOD

This paper develops an approach to urban demand prediction that makes use of far more limited, but more readily available building information: total floor area and building type. Archetype building models were then employed to generate disaggregated, time-varying energy demand profiles for specific building types, which could then be scaled, combined and transformed to produce a time varying electrical demand profile for a group of buildings connected to a substation. The benefit of this approach is that the archetype models are already populated with data from a variety of sources and represent 'typical' UK non-domestic buildings (e.g. Jenkins et al, 2007). The accuracy of the approach is critically analysed and its advantages and limitations highlighted.

For the purposes of this study, six basic building types were used: retail premises, offices, hotels, pub/club, restaurant and high density housing; these correspond to those identified by the utility Scottish Power Energy Networks (SPEN, 2015) as connected to their urban substation network. For each of these, a simulation model was developed on the ESP-r building simulation tool. ESP-r allows the energy and environmental performance of the building and its energy systems to be determined over a user defined time interval (e.g a day, week, year) and explicitly calculates all of the energy and mass transfer processes underpinning building performance. An exhaustive description of the theoretical basis of ESP-r is provided by Clarke (2001), amongst others.

Substation Profile Generation

Each archetype was simulated to produce, eighteen disaggregated demand profiles, comprising 3 x 6 1-week sets for typical transition, summer and winter weeks (Table 1) using a Glasgow test reference year climate data set, at half-hour time increments. These were then normalised for floor area.

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

Scaling was based on the total floor area of each archetype connected to a substation. Additionally, based on evidence from the literature, it was assumed that 0.85 of the connected floor area was actively serviced (i.e. contributes to energy use) (CIBSE, 2010) and that there was a 0.9 occupancy rate (Jones Lang Lasalle, 2013). Thus for any building type i with a load j, the scaled demand (W) at some time t, $D_{i,j}(t)$, is given by:

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

Where $D_{i,j-b}(t)$ is the normalised demand in the base profile (W/m^2), 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 involved subdividing each scaled profile into up to 20 components. Each component was then time 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 $\sigma = \frac{6}{\pi}$, derived from comparison and calibration with monitored data, outlined later.

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

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

$$\boldsymbol{D''}_{i,j} = \sum_{t=0}^{t=168} \sum_{k=1}^{k=n} \boldsymbol{D'}_{i,j,k}(t) \qquad (4)$$

Where $\boldsymbol{D}_{i,j}$ is the original electrical demand profile vector for building type i, load type j; $\boldsymbol{D'}_{i,j,k}$ is a subdivided electrical demand profile and k is between 1 and n; n being the number of profile subdivisions (minimum 5 and maximum 20). $D_{i,j,k}$ is the subdivided demand at a specific time interval. R is the random time-shift. Note that if $t + R > 168$ $t = t + R - 168$; also, if $t + R < 0$ $t = 168 + R$.

$\boldsymbol{D''}_{i,j}$ is the reconstituted, diversified profile.

Transformation of the archetype profiles was undertaken for a variety of purposes i.e. transformation of thermal demand profiles was required in order to generate a corresponding electrical profile. For example, where heating demand was met using a heat pump, the thermal demand profile could be transformed to equivalent electrical demand profile using:

$$D'''_{i,j}(t) = f_{HP}\frac{D''_{i,j}(t)}{COP(t)} \qquad (5)$$

$D'''_{i,j}(t)$ 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_{HP} is the fraction of the simulated heat load met by heat pumps. Similar transformations were employed to determine

CHP generation profiles, or to generate corresponding cooling demand profiles.

Supplementary profiles were also generated to enable the impact of EVs and increasing penetration of PV to be assessed. These were generated using pre-existing ESP-r high resolution models (e.g. Hand et al., 2014)

The final substation load is the summation of each scaled and diversified archetype building type electrical demand profile, along with the supplementary profiles. So, the load at the substation at some time *t* would be:

$$D_{sub}(t) = \sum_{i=1}^{i=n}\sum_{j=1}^{j=m}(D'''_{i,j}(t) + P'''_{i,j}(t)) + D_{EV}(t) + P_{PV}(t) \quad (6)$$

Where *n* is the number of building types connected to a substation and m is the number of building load types. Using the pre-generated building load profiles as a starting point and the data specifying the case to be modelled, the profile tool was used to generate aggregate substation load profiles. Note that for load which only require scaling and diversification such as appliance loads $D'''_{i,j}(t) \equiv D''_{i,j}(t)$.

The substation profile is the sum of the individual archetype profiles. The method for generating the profile for each archetype is summarised in Figure 1. This is the approach encapsulated in the profile tool.

VERIFICATION

The profile generation approach outlined was compared to real data collected for six substations in Glasgow city centre (Labelled Substations A-F) at half hour time intervals over a year. Using this data, three averaged weekly demand profiles for a winter, transition and summer week were produced. Six corresponding substation profiles were generated, based only on estimates of the floor area of each building archetype connected to a particular substation and these were compared to the measured profiles.

The following assumptions were used as initial input to the profile tool. It was assumed that 20% of heating demands were provided by direct electric heating; the remainder from gas heating systems (DECC, 2015), 20% of the total floor area was air conditioned (Pout et al, 1998), power generation from CHP and PV, and power demand from EVs were all assumed to be negligible.

An initial review of the generated profiles indicated that they tended to overestimate the magnitude of the demand. Further, the profile shape was a poor fit. Subsequent simulations were undertaken to identify the standard distribution for temporal load diversity that provided the best match to the monitored profiles; this turned out to be $\sigma = 6/\pi$.

A more methodical comparison was then undertaken looking at the differences and degree of correlation between the modelled and the monitored profiles. The two metrics used in this comparison were as follows.

The mean difference between the monitored (half-hour averaged) seasonal profiles (expressed as a percentage); this was calculated as follows:

$$D = \frac{100}{N}\sum_{i=1}^{i=N}\left(\frac{P_i - S_i}{P_i}\right) \quad (7)$$

Where N is the number of data points in the profile (336), P is the monitored total power demand at some point in time; S is the corresponding simulated total power demand at the same point in time.

The correlation between the profiles was calculated using:

$$CC = \frac{\sum_{i=1}^{i=N}(P_i - \overline{P})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{i=N}(P_i - \overline{P})^2 \sum_{i=1}^{i=N}(S_i - \overline{S})^2}} \quad (8)$$

The correlation coefficient gives an indication of the how well the modelled profiles reflect the shape of the monitored profiled.

The mean difference between modelled and monitored profiles shown in Table 2 is less than 20% in most cases – this includes errors in magnitude and temporal errors between the real and simulated data. The errors in the table include both over and under estimation of demand: positive and negative values, respectively. This level of error is relatively low, given the significant uncertainty associated with modelling the demand of multiple buildings, the lack of specific data associated with the building stock and demand drivers such as climate and occupancy. By comparison, Menezes et al (2010) highlight underestimation of building demand of up to 70% when modelling the energy performance of individual buildings.

However, there are two substations where the difference between the profiles is significantly greater than in the other cases. For Substation A, the demand drops significantly in the transition and summer months; this was not reflected in the modelled results. The possible reason for this was that the substation is located in an area with many college and university buildings and consequently demand will be lower outside term time when occupancy of educational buildings is low. Additionally, the demand associated with Substation E is significantly larger than that modelled and is also larger than would be expected for the floor area given. The mean load predicted was approximately 25W/m^2 of estimated floor area. The modelled mean demand was approximately 9W/m^2. The mean measured demand for another comparable substation (Substation B) which served office buildings was also 9W/m^2. This would indicate that either, there is an unusual level of demand occurring at Substation E or (more likely) that the connected floor area was significantly underestimated.

The correlation coefficient for the modelled profiles is generally greater than 0.9, indicating that there is a good temporal match between the modelled and measured data in terms of the rise and fall in demand. However, the correlation between profiles appears to be weakest

for Substation F, where the demand falls off very slowly in the evening – something that cannot be replicated using the archetype models. The buildings connected to substation F are associated with a large retail development and the slow fall off in the profile is likely to be associated with late night opening. The mean difference in demand estimation is approximately 15%.

The 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 unusual demand characteristics or poor estimations of floor area could lead to significant discrepancies between the simulated and modelled data.

MODELLING FUTURE DEMAND

The profile tool was then used to assess possible, future changes to substation electrical loads in Glasgow City centre. Glasgow city centre is representative of many other cities in the UK, in that it is dominated by retail and office buildings, with some high-density housing and entertainment venues.

The future demand assessment was based on five scenarios – a base case and four future scenarios outlining possible changes to UK urban areas up to 2050. The four future scenarios were derived from work undertaken by UK National Grid (2016). These were:

- *gone green*: "New technologies are introduced and embraced by society enabling all carbon and renewable targets to be met. "
- *no progression*: "…low economic growth, traditional sources of gas and electricity dominate with little innovation affecting how we use energy."
- *slow progression*: "… limited innovation money available is spent on renewable and low carbon technologies and there is limited government money to support development. "
- *consumer power*: "… relative wealth, fast paced research and development and spending. Innovation is focused on meeting the needs of consumers, who focus on improving their quality of life."

The translation of these scenarios into inputs for the profile generation tool are shown in Table 4 These were derived from literature review or (in the case of future conditions) agreed with SPEN. Further, floor area data for all secondary substations in Glasgow city centre was made available by SPEN (2015). This is summarised in Table 3.

The city centre area is served by over 200 secondary substations, with capacities ranging from 500 kVA to 6000 kVA. To keep the modelling and data analysis process manageable, a subset of 42 substations was selected. This comprised 4 of the 6 substations used in the verification activity along with 38 substations with differing mixes of archetype buildings connected to them: those with a) near average floor areas of each archetype buildings and b) those with higher than average and below concentrations of specific building archetypes. The selection also accounted for the shortcomings of the modelling approach highlighted previously: so substations in areas where late night shopping could take place and those in the locality of college and university buildings were not selected. Finally, 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 of the 42 substations selected for a typical winter and summer week using the tool. Consequently a total of 420 substation profiles were generated and analysed. Figure 2 illustrates the changing form of the electrical demand profiles produced for one substation for a summer week under the different scenarios modelled. The evident oscillations in the future demand profiles are due to EV charging events.

RESULTS AND DISCUSSION

The key parameter assessed for each scenario and for each substation in the sample was the peak demand appearing in the data. Projected peak demand is the key variable 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 modelled, for each secondary substation and for the summer and winter weeks. This was calculated as follows.

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

Where $\widehat{D_s}$ is the peak demand occurring in the scenario and $\widehat{D_b}$ is he peak demand seen in the base case.

Initial analysis of the results indicated that at 7 substations there were triple digit increases in demand (Figure 3). Closer investigation showed that these were substations with small floor areas and low building-related loads. The addition of EVs into the assessment resulted in a very substantial increase in demand compared to the base case. Removing these substations from the results gave a more representative indication of the likely changes in demand that the majority of substations may experience.

Figures 4 and 5 show the change in peak demand for all scenarios in winter and summer, for all substations, excluding those with small connected floor areas.

Figure 4 shows the changes in winter demand with those substations with the smallest floor area removed. The median changes in winter peak demand are +35% for Gone Green, +5% for No Progression, +6% for slow progression and +32% for Consumer Power. Figure 5 shows the same information for the summer peak demands. Again, the presence of EV's results in some very high changes in peak demand relative to the base case. Median changes in demand are +6% for gone green, +8% for no progression, +1% for slow progression and +28% for consumer power.

It is evident from both figures that the picture of changing demand is a complex one, with increases and

decreases in the level of peak demand evident in both summer and winter. Consequently, each scenario was analysed in isolation in order to identify the impact on peak demand and the underlying causes.

Gone Green - Figure 6 shows that the majority of substations show an increase in winter peak demand; those substations with a low initial demand level experience a very significant increase in demand relative to the base case due to demand from EVs. A minority of substations see a drop in demand; these were substations with significant floor areas of office or retail space attached to them. In these cases, the reduction in building heating, lighting and small power demands associated with improved energy efficiency outweigh any increase in peak demand due to EVs. In summer (Figure 7) the results is variable with many substations showing an increase in demand, the increase being mainly due to EVs as was the case in winter. However, more substations show a reduction in peak demand than was seen in winter. These were substations with larger floor areas connected to them, which have a correspondingly larger input from PV, offsetting the increase in demand due to EVs and increased cooling.

No Progression - There is very little change in the peak demand other than in those few cases where there was a low substation demand in the base case; in these instances, the charging of a small number of EVs makes significant difference to the peak. Figure 8 shows the typical change in winter peak demand. Summer peak (Figure 9) demands also show little change compared to the base case other than where there is a combination of EVs and low base case loadings. Where there are any slight reductions in peak demand due to output from the small amount of installed PV offsetting coterminous demand from cooling and appliances.

Slow Progression - the winter week shows significant increases in the peak demand when low base case demand was coupled with EVs; however, there are also many substations that show a substantial drop in peak demand (Figure 10). The reductions in peak demand occur where demand side reduction measures (prevalent in this scenario) such as energy efficient appliances, improved building fabric and lighting control outweigh increases in demand due to increased EV. In the summer week, there is a mixture of increased peak demand (with due mainly to EVs) and decreased peak demands. The decreased demand is most evident in those substations where the demand side reduction measures outweigh the effect of increased EV demand – typically where there are significant retail and office floor areas connected to the substation.

Consumer Power - the results are relatively consistent for the winter week (Figure 12), showing that almost all substations were subject to increased or unchanged demand; this is a result of the combination of increased appliance loading and (again) increasing numbers of EVs. In the few cases where the peak demand was slightly reduced, output from PV and CHP directly offsets demand peaks due to EVs; this tended to be restricted to substations with larger floor areas of buildings connected to them. In the summer week (Figure 13) the Consumer Power scenario all substations show increased peak demand due to a combination of increased EV charging, increased cooling loads and increased appliance demands; these are not offset by PV and CHP generation.

CONCLUSIONS

A pragmatic approach to the prediction of substation loads has been developed that uses archetype buildings, building simulation predictions of their thermal and electrical demand and estimations of the floor area of each archetype connected to substations. This data was scaled, diversified transformed and combined to generate aggregate electrical demand profiles for substations. The approach has been encapsulated in a profile tool.

The profile tool's predictions were compared to empirical measurements of substation load, with predictions generally within +/- 20% of measured data. However, the results are dependent upon estimated floor area and the characteristics of the connected building stock being similar to the archetype models.

The future demand for a representative set of substations was modelled for a base case and four future electricity network scenarios: No Progression, Slow Progression, Gone Green. These scenarios allowed multiple potential changes to the built to be assessed in combination

The No Progression scenario resulted in peak demands very similar to those seen in the Base Case.

In the Slow Progression scenario, the introduction of a modest number of EVs led to increased demand in some substations. In substations with high base case demands, a combination of fabric and appliance energy efficiency measures resulted in curtailment or even reduction in demand in summer and winter.

In the Gone Green scenario, substations with a low existing base load showed a substantial increase in demand due to the introduction of EVs. In substations with a large connected floor area of buildings, Gone Green's combination of reduced appliance demand, improved fabric and microgeneration and lighting control combined to reduce demand, sometimes substantially.

The Consumer Power scenario resulted in every substation showing and increase in peak demand in summer. Only in cases where there was a substantial winter heating load did the Consumer Power scenario show cases where peak demand was reduced – in these cases the output from CHP offset those factors tending to increase demand such as increased use of appliances and growth of EVs.

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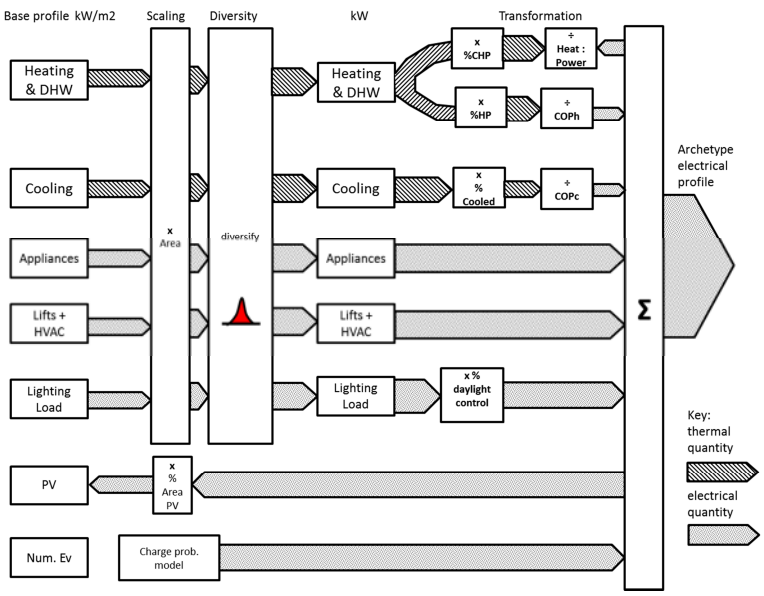

Figure 1: Schematic, illustrating the general approach to profile generation.

Table 1: profiles generated for each archetype.

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

Table 2: differences and correlation between modelled and measured substation profile data.

Substation	Sub A Winter	Sub A Transition	Sub A Summer	Sub B Winter	Sub B Transition	Sub B Summer	Sub C Winter	Sub C Transition	Sub C Summer
Mean difference %	20.6	45.9	99.1	-9.3	-5.6	-1.4	-16.5	-21.9	-21.2
Correlation	0.92	0.95	0.95	0.84	0.93	0.95	0.81	0.93	0.92
Substation	Sub D Winter	Sub D Transition	Sub D Summer	Sub E Winter	Sub E Transition	Sub E Summer	Sub F Winter	Sub F Transition	Sub F Summer
Mean difference %	-16.2	-13.4	-15.1	-64.6	-66.5	-66.7	14.7	16.9	14.6
Correlation	0.92	0.96	0.96	0.89	0.95	0.96	0.62	0.75	0.82

Table 3: Estimated floor areas per archetype for Glasgow City Centre secondary substation network: from SPEN dataset.

**Figure includes educational and administrative buildings.*

	Retail	Hotel	Bar/pub	Restaurant	Office*	Domestic
Floor area m^2	432,600	83,900	60,160	65,600	1,006,000	33,000

Table 4: details of base case and future scenario data inputs.

		Future Scenario			
	Base Case	Gone Green	No Progression	Slow Progression	Consumer Power
Electric heating	The vast majority (80%) of space heating and hot water heating is provided by gas boiler systems, with around 20% of hot water and space heating is provided by direct electric heating. Palmer and Cooper (2012), DECC (2015), Pout et al (1998).	Significant investment in heat pumps and replacement of all electric heating. 50% of space and water heating by heat pump. 0% direct electric.	Continued reliance on fossil fuels or direct electric heating. 80% of space heating gas, 20% direct electric.	Heat pumps generally too expensive for significant uptake some replacement of direct electric for cost reduction. 80% space heating by gas 10% heat pump, 10% direct electric	Limited interest in heat pumps, gas continues to be dominant heat source. 80% space heating by gas 10% heat pump, 10% direct electric
Electric cooling	Around 20% of the floor area connected to city centre substations is actively cooled (Pout et al, 1998).	Limited growth in cooling due to energy efficiency drive. 25% of floor space is cooled.	Limited uptake of cooling technologies due to cost. 25% of floor space is cooled.	Limited uptake due to increased energy efficiency and high cost. 25% of floor space is cooled.	High demand for air conditioning due to increased comfort expectations and rising temperatures. 40% of floor space is cooled.
Electric vehicles	No EV charging (Next Greencar, 2016)	1/6 of vehicles are EVs by 2035. Up to 50 in a substation area.	Very limited uptake of EVs due to limited funds for investment. Up to 5 EVs at a substation area.	Hybrid vehicles preferred to full EV due to limited funds. Up to 20 EVs in a substation area.	Growth in demand for EVs as luxury item. Up to 30 EVs in a substation area.
Appliance demand	Appliance demand representative of existing buildings (BRE, 2009)	Appliance demand reduced due to energy efficiency drive. 25% reduction in appliance demand.	Demand remains static, limited investment in energy efficiency. No reduction in overall appliance demand.	Demand reduced due to preference for energy efficiency. 25% reduction in appliance demand.	High demands for consumer appliances, limited focus on energy efficiency. 20% increase in appliance demand.
Building fabric	Representative of existing buildings (BRE, 2009)	Tightening of building regulations towards zero-carbon new build. 40% of buildings significantly upgraded.	Little investment in building fabric improvements only new build are improved. 10% of buildings upgraded.	Tightened building regulations and investment in retrofit. 30% of buildings upgraded.	Little investment or interest in demand reduction only improvements in new build. 10% of buildings upgraded.
Lighting control	Assumed negligible.	Significant use of lighting control due to drive towards energy efficiency and carbon reduction. 50% of lighting systems controlled.	Low uptake of new technologies. 5% of lighting systems controlled.	LED lighting and lighting control popular demand reduction options. 40% of lighting systems controlled.	Little interest in energy efficiency, gradual uptake of LED and control. 5% of lighting systems controlled.
PV and CHP	Assumed negligible (OFGEM, 2016)	High investment in micro-CHP, DH-CHP and PV. 5% of roof area PV, 25% of heating load from CHP.	Low uptake of new technologies continued reliance on existing systems. 1% of roof area PV, 0% of heating load from CHP.	Limited uptake of microgeneration due to limited funds. 2% of roof area PV, 10% of heating load from CHP.	Small scale generation popular as income source accounts for 1/3 of all capacity by 2020. 5% of roof area PV, 25% of heating load from CHP.
Appliance energy efficiency	Appliance demands representative of current case (BRE, 2009)	Switch over to low demand appliances, lighting transitions to LED. 25% reduction in appliance demand.	Little investment in energy efficiency, static demand. 5% reduction in demand.	Preferred means to reduce emissions due to lower cost. 25% reduction in demand.	Little interest in energy efficiency, appliance use is increased. 20% increase in demand.
Load shifting	No load shifting.	Significant uptake of time of time of use tariffs and load shifting. 40% uptake of load shifting.	Consumers not engaged with load shifting. 0% uptake of load shifting.	Some uptake of time of use tariffs. 20% uptake of load shifting.	Limited interest in load shifting other than as a means to maximise revenue from CHP. 10% uptake of load shifting.

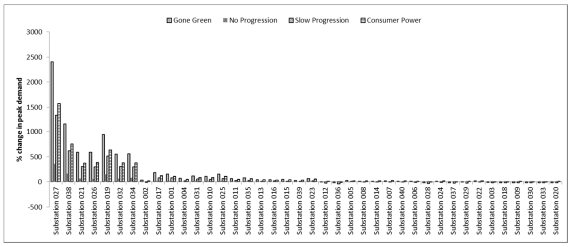

Figure 3: change in winter peak demand with substations ranked by total connected floor area.

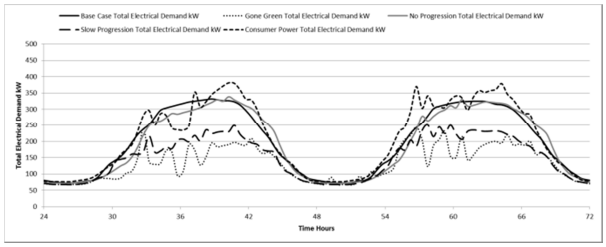

Figure 2: Illustration of changing demand profiles under different scenarios modelled.

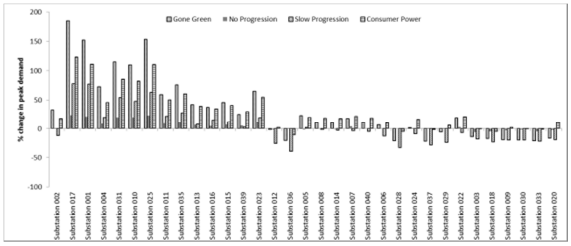

Figure 4: all scenarios: change in winter peak demand (substations with small floor area removed).

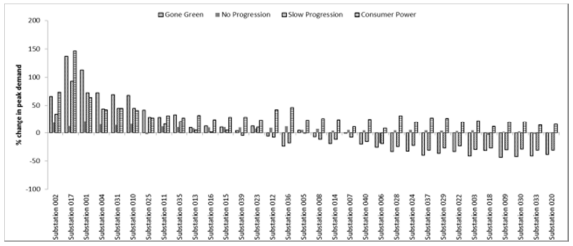

Figure 5: all scenarios: percentage change in summer demands (substations with small floor area removed).

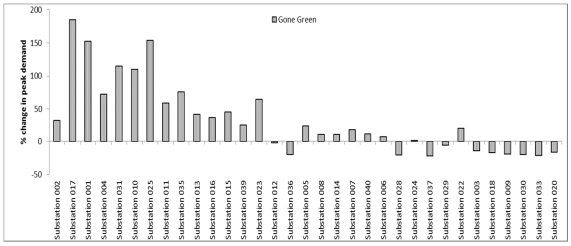

Figure 6: Gone Green scenario: change in winter peak demands (substations with small floor area removed).

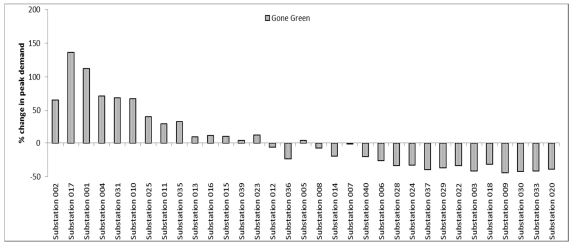

Figure 7: the effect of the Gone Green scenario on summer peak demands (substations with small floor area removed).

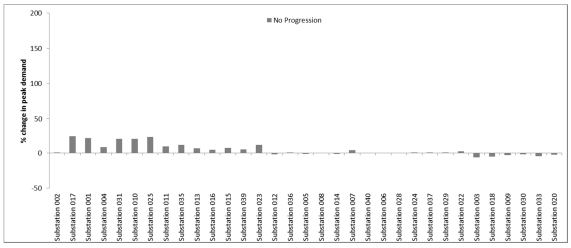

Figure 8: change in winter peak demands relative to base case for the No Progression scenario (substations with small floor area removed).

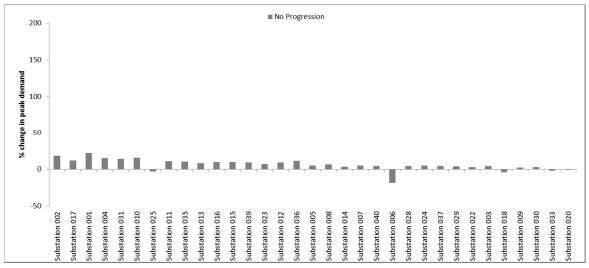

Figure 9: change in summer peak demands relative to base case for the No Progression scenario (substations with small floor area removed).

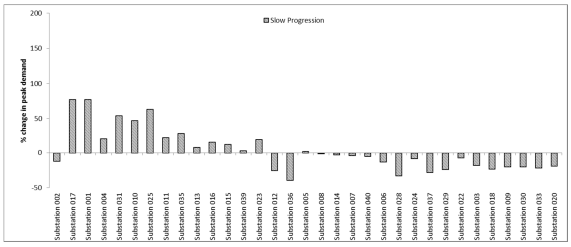

Figure 10: changes in winter peak demand relative to the base case for the Slow Progression scenario(substations with small floor area removed).

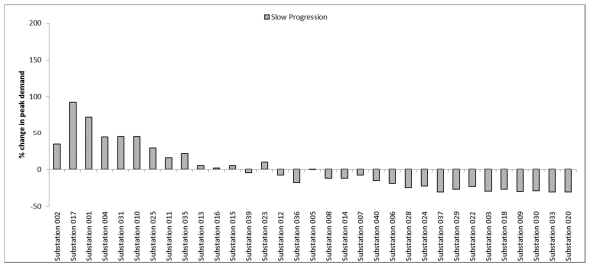

Figure 11: changes in summer peak demand relative to the base case for the Slow Progression scenario(substations with small floor area removed).

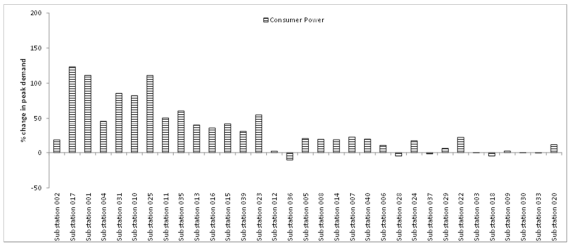

Figure 12: change in winter peak demand relative to base case for Consumer Power scenario(substations with small floor area removed).

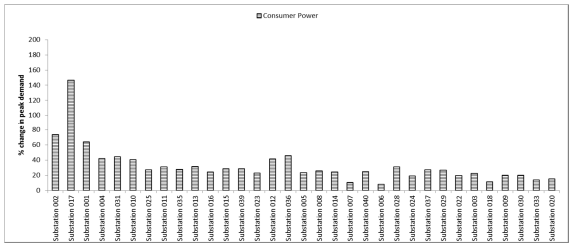

Figure 13: change in summer peak demand relative to base case for Consumer Power scenario(substations with small floor area removed).