

GRANULAR AUCKLAND CUSTOMER MODEL: LINKING SOCIO-ECONOMIC AND DWELLING DATA TO ENERGY USE

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Overview

In this paper, we propose that data-driven bottom-up modelling has become essential to understand at customer-level the interaction between energy usage, dwelling characteristics and socio-economics. Various energy usage models are employed in the energy industries across the developed world but often these tend to be top-down models with low granularity and driven mainly by generalised macro-economic assumptions [1]. Customer behaviour and requirements are increasingly varied, individualistic, and do not adhere to one-size-fits-all assumptions [2]. Also, customer deprivation [3] and pre-existing dwelling characteristics impact customer decisions to adopt certain technologies, which can only be captured bottom-up by fusing energy usage data with physical dwelling and socio-economic information.

Methods

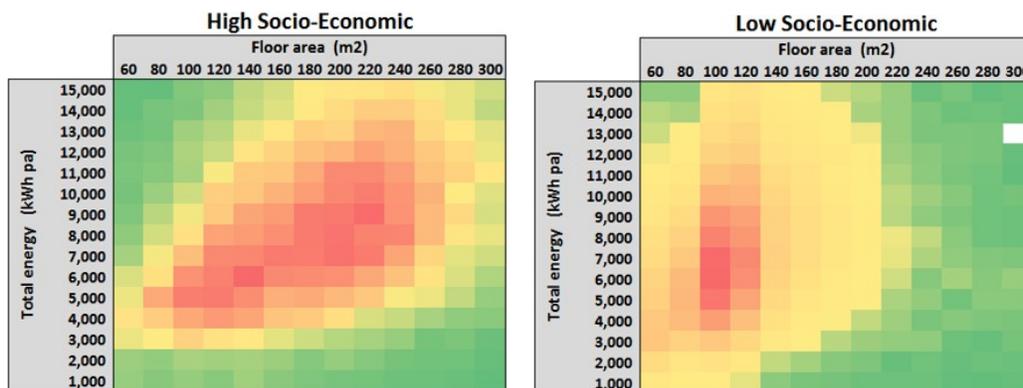
The approach used involved building a ‘Granular Auckland Customer Model’ for the Auckland region, which includes roughly 1,5 million people or 600 000 residential electricity connections (referred to here as customers) in urban, suburban and rural areas. The model fuses different datasets at individual customer level bottom-up, including customer’s spatial location, historically billed monthly energy usage (including gas and electricity), national census information (e.g. income, family makeup, employment, tenure), dwelling characteristics (e.g. type, dwelling material, age, size) and half-hourly load profiles for peak days. The resulting ‘Granular Auckland Customer Model’ provides a convenient and efficient platform for analysis using statistical and data science techniques.

Results

Some key results from the ‘Granular Auckland Customer Model’ include:

Energy usage by deprivation. One of the main drivers for residential energy usage is dwelling size. The heat maps in Figure 1 show individual customer energy usage by dwelling floor area for high and low socio-economic geographical areas. The colour range of the heat maps indicate the number of dwellings as a percentage of the total number of dwellings in each dataset i.e. red means a high percentage of properties and green means a low percentage of dwellings. While total energy usage increases with floor area for low and high socio-economics, the distributions are quite different. High socio-economic areas tend to use more energy per dwelling due to the fact that dwellings in high socio-economic areas are larger than dwellings in low socio-economic areas. Interestingly the heat maps also show that for the same floor area, lower socio-economic dwellings tend to use more energy than high socio-economic dwellings. Further preliminary analysis indicates that important drivers of this phenomenon could be higher occupancy rates and lower energy efficiency levels.

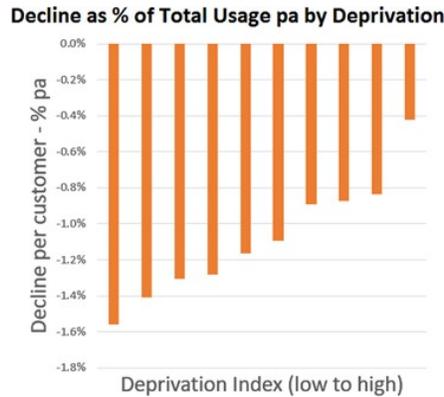
Figure 1. Residential energy usage and dwelling floor areas for high and low socio-economic households



Energy usage by deprivation over time. Our analysis finds that the decline in energy usage per customer (observed in Auckland as well as in many other parts of the developed world) has not been uniform across all

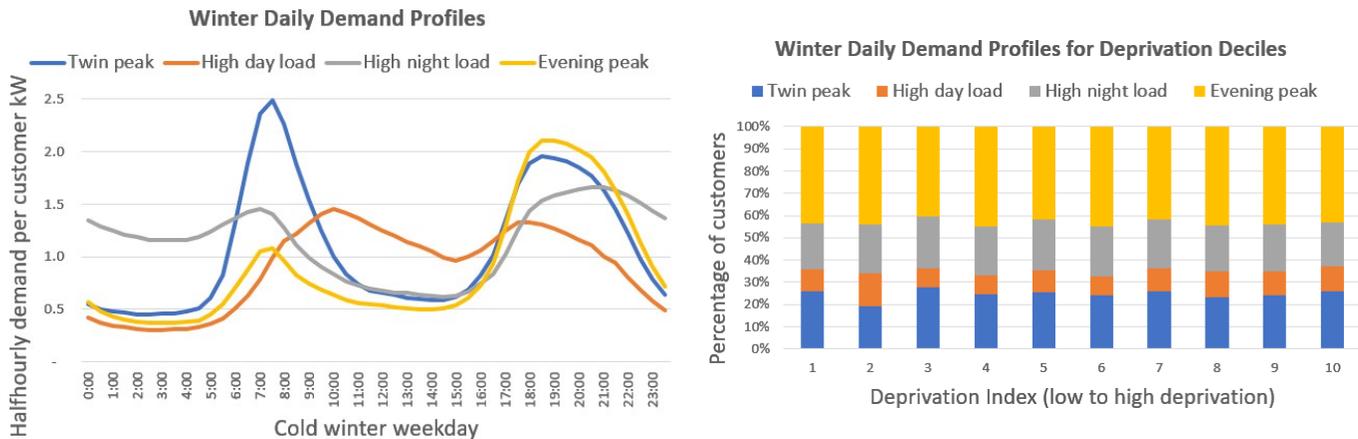
customers groups. Average kWh decline rates over the last 10 years range from 0 to 200 kWh pa. As a percentage of total usage, it is very similar across the total usage range – in the order of 1% pa. However, the decline in energy usage decreases with increasing deprivation (Figure 2) (i.e. reduction of social wealth). Energy usage for residential customers in low deprivation areas (correlated with high-socio-economic areas) have declined at about 3 times the rate of customers in high deprivation areas (correlated with low-socio-economic areas).

Figure 2. Declining trend in residential energy usage per customer over the last 10 years by deprivation index.



Peak demand assessments. Figure 3 shows four common residential load profiles for residential customers on the Auckland electricity network during network peak times developed using data mining clustering algorithms. Network peaks usually occur on a limited number of days and half-hours during the coldest winter days. The profiles demonstrate the significant variation in residential customers behaviour. Most importantly, the analysis found that the four key load profiles exist across all levels of deprivation. From a network investment perspective and cost allocation perspective, this is an important finding.

Figure 3. Typical residential half-hourly load profiles during network peak times and distribution of typical residential half-hourly load profiles across areas with different deprivation indices



Conclusions

This paper demonstrated the capability of bottom-up modelling and analysis informed by rich granular data to provide customer-usage trends. For our 600 000 customers, we have discovered considerable differences in how residential customers use energy based on dwelling characteristics and socio-economic indicators.

References

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