Towards a High-Resolution, Stochastic, Domestic Energy Demand Model to Assess the Local Network Impact of Heat and Transport Electrification

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Abstract

Electrification of domestic heat and transport will significantly increase loading on the distribution network. Understanding the capacity implications will require an increased focus on the impact of individual household behaviours. A high resolution domestic energy model has been developed for the assessment of demand at the individual distribution network feeder scale. At this level stochastic variation in multiple elements (e.g. occupancy, appliance ownership, use timing, heating type, vehicle mileage etc.) are all important in determining the demand profile at different timescales. Modules have been incorporated for each stochastic element, with significant input flexibility to alter behaviour and technical assumptions. The output from the model indicates that understanding use behaviours, particularly heating and EV charging behaviours, will be critical for understanding potential impacts at the local level and to ensure that maximum demand assumptions account for local conditions.

Introduction

That increasing electrification of domestic heat and transport demand will impact the capacity limits and operating characteristics in the distribution network is understood, however, models that simulate the impact accurately, including the potential variability at smaller scales, are required.

Increased domestic demand electrification will impact at all grid scales, including low voltage feeders (Low Carbon London (2014), Vivid Economics (2019)). The main impact will be on peak loading, particularly if the additional loads for heating and transport are unconstrained. The increase in the peak can be mitigated by controls that aim to shift some demand away from the peak periods (e.g. at-home EV charging can be scheduled overnight) or by time-of-use tariffs. However, if poorly understood and implemented, these may only shift the peaks to a different time period.

Without electric heating or vehicle charging, the peak design load for an individual household is typically 18kW (based on a 80A connection). The current peak design load for a network reduces significantly with scale as individual household peak loads are rarely simultaneous. This is known as After Diversity Maximum Demand (ADMD) and is used by Distribution System Operators (DSO) for system design. The expected peak load reduces to c.2kW per household at 100 households (Barteczko-Hibbert, 2015).

The number of houses connected to low voltage feeders can vary significantly from low numbers to 100+ (Hattam and Greetham, 2017). At this level, the stochastic behaviour of individual households will be a factor, requiring a different resolution of demand modelling than has been typically used for larger scale modelling requirements.

Existing Models

High resolution, domestic-scale models with electricity, heat and hot water outputs are rare. The primary open-source UK model is the ‘Crest’ model (McKenna and Thomson, 2016), but the calibration basis for the model lacks the per-household differentiation required for stochastic modelling of variation in demand between households (Flett, 2017). Diversity assessment at small scale (sub-100 houses) requires the variation to be assessed and compared probabilistically.

Aim

The aim of this work is to develop a flexible, high resolution tool for assessing the impact of further electrification of domestic energy use at the household scale. A modular, bottom-up approach, incorporating several existing validated elements, ensures it can be modified on an ongoing basis as new behavioural data emerges.

Model Development

An integrated stochastic assessment tool has been developed in Python that combines two principal existing ESRU software packages: domestic occupancy, appliance and hot water demand from the ‘OccDem’ model and a black-box building thermal model from the ‘IDEAS’ model. In addition, a stochastic car use model has been developed to assess charging fre-

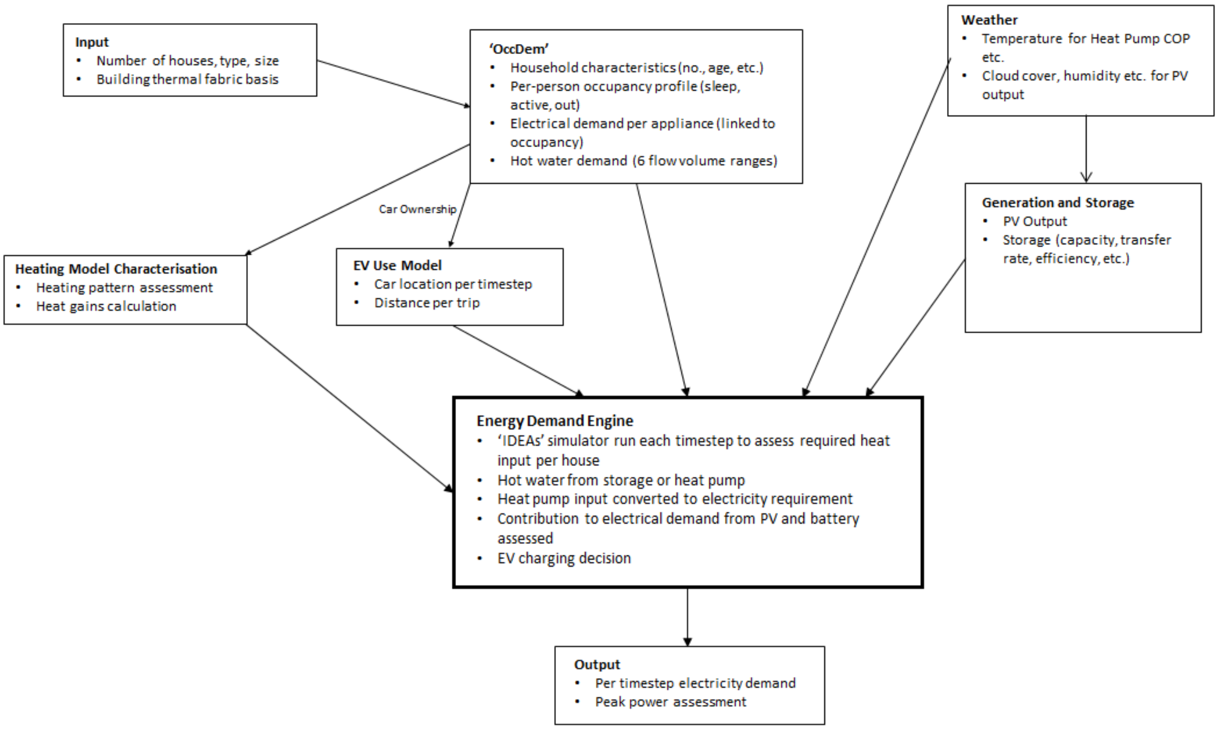


Figure 1: Overall model structure

quencies for EV vehicles and a overall simulation engine develop to assess demand and control actions per timestep.

Figure 1 shows the structure and calculation sequencing for the overall model, with each module described below.

Occupancy and Demand 'OccDem'

The existing 'OccDem' model (Flett, 2017) is publicly available. The model is highly stochastic and separately calibrated for a variety of household types, with the aim to produce occupancy, appliance and hot-water demand profiles that are representative of individual households. This was achieved by additional statistical manipulations in comparison with other models that typically use population-level probability models that converge to the population average (Flett and Kelly, 2021).

This model allows for the generation of 1-minute resolution profiles for both total electricity and hot water demand, or demand differentiated by appliance or hot water volume range.

Heating Model Characterisation

Heating behaviour modelling is complex and currently lacks comprehensive data differentiated by household types. The Household Electrical Survey (Zimmermann et al., 2012) included temperature data over several months. Using the method defined in (Huebner et al., 2013), the data was analysed for heating patterns. Five broad patterns were evident (no pattern/manual, always-on, waking hours, two-period (morning+evening), one-period (evening)), with some additional variation in terms of setpoint temperature variation and the likelihood of manual boost heating outside of the normal pattern. Within the model these base patterns are applied probabilistically, principally for gas boiler use patterns.

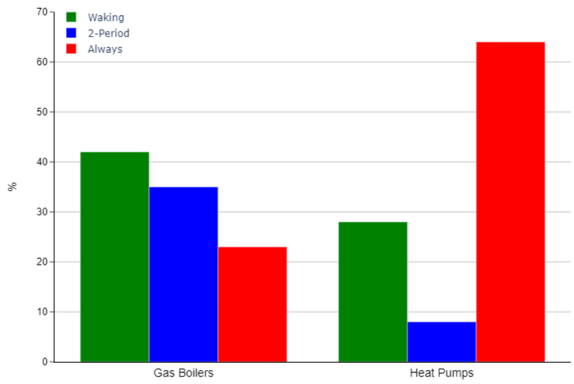


Figure 2: Typical heating patterns from EDRP and RHPP datasets (from Watson et al. (2021))

There is evidence from data gathered from over 400 households with heat pumps from the Renewable Heat Premium Payment (RHPP) scheme (2013-2015) (Lowe, R., Department of Energy and Climate Change, 2017), that heating use patterns were different for heat pump users in comparison with traditional gas boilers. Watson et al (Watson et al., 2021) identified three broad heating patterns from both the

RHPP data and the gas-heating Energy Demand Research Project (EDRP) dataset with 6600 households (AECOM Building Engineering, 2018) . These were waking hours, two-period and always-on. Gas households had a 42/35/23% split, and the equivalent for heat pump households was a 28/8/64% (see Figure 2). The result is a significant increase in overnight and mid-day demand and a lowering of the morning and early evening peak demand. Further data is required to fully confirm if this pattern is a inherent feature of heat pump use, or a feature of the predominantly social housing RHPP population.

To allow the model to be used both to predict energy demand with heat pumps and to be used as a tool to understand the impact of different operating pattern, the proportion of households with each pattern type and temperature setpoints can be modified.

It is assumed that for households without an 'always-on' heating pattern, there is at least a partial correlation between typical occupancy patterns and heating timing. The 'OccDem' occupancy model incorporates stochastic waking and sleep times for individuals. Heating schedules are linked based on the probabilistic base pattern with variable offsets (i.e. 30-90mins before waking). There is no current dataset that links occupancy and heating schedules. However, further validation is planned against the general heating patterns captured by the Energy Follow-Up Survey (Department of Energy and Climate Change, Building Research Establishment, 2016).

EV Use Model

National Travel Survey (NTS) data (Department of Transport, 2018) has been used extensively for vehicle use modelling and specifically for EV charging models. Travel survey data is considered representative of EV use data in the absence of comprehensive EV datasets (Pareschi et al., 2020).

Daily car use for the majority of households is significantly below typical EV ranges, and battery capacities are increasing, therefore it is considered a reasonable assumption that use patterns will not change significantly. The focus on vehicle use with charging decisions treated separately allows the model to be recalibrated for different charging behaviours without significant modification of the underlying mileage model.

The current model incorporates NTS data from 2002 to 2017 and has a total of 4.45 million individual journeys. Data up to 2020 is available. Filtered for journeys as the household car driver, this reduces to 2.04 million relevant journeys.

For multiple car households in the NTS data, the car used is not identified. For initial analysis, the use by the highest user by distance is used as a proxy for a main car EV. Further work is required to determine how EV use in multiple car households should be modelled, but this work assumes a single EV per household used as the main car.

#	Start Time.	End Time	Dist. (miles)	End Location
		19.21		*Home(1)*
1	08.32	08.57	10	Public Charger(3)
2	09.12	09.28	7	Work(2)
3	16.37	16.59	9	Home(1)

Table 1: Example car use output (inc. previous day end time/location)

As per the 'OccDem' model the dataset has been split into a complementary set of multiple household types. 20 sub-populations are defined based on employment status, household type, number of owned cars and number of licensed drivers.

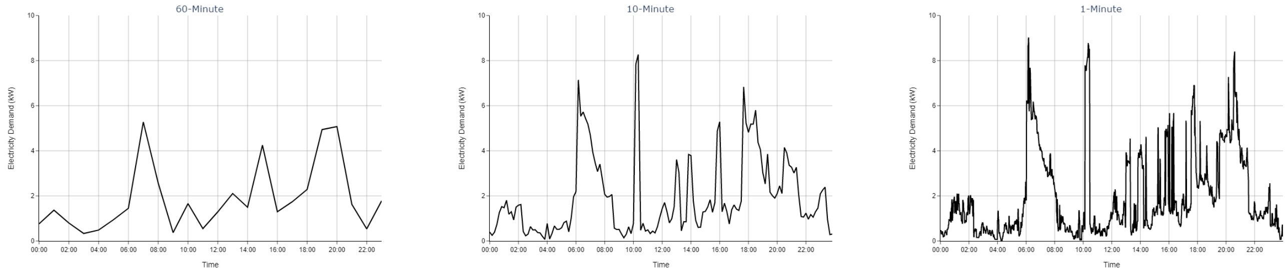
The following data was generated for each household:
(1) average distance per day
(2) average number of daily car journeys
(3) daily zero use probability
(4) maximum number of daily journeys
(5) standard deviation of journeys per non-zero day
(6) maximum total daily distance
(7) standard deviation of distance per non-zero day
(8) skewness of daily distance per non-zero day

From this data, a number of probability models were generated to allow average and variation in number of journeys and distance to be determine for each modelled household. The average distance per day is the primary statistic generated for each household and the main driver in determining charging requirement when not in use.

The NTS data also includes a 'purpose' for each journey. 23 potential purposes are available, including commuting, food shopping, entertainment etc. For EV modelling the location of the car when not in use is critical information for at-home vs. public station charging. The purposes have therefore been simplified to four assumed destinations (home(1), work(2), locations where public charging availability is likely (education, shopping) (3) and all other locations (4)).

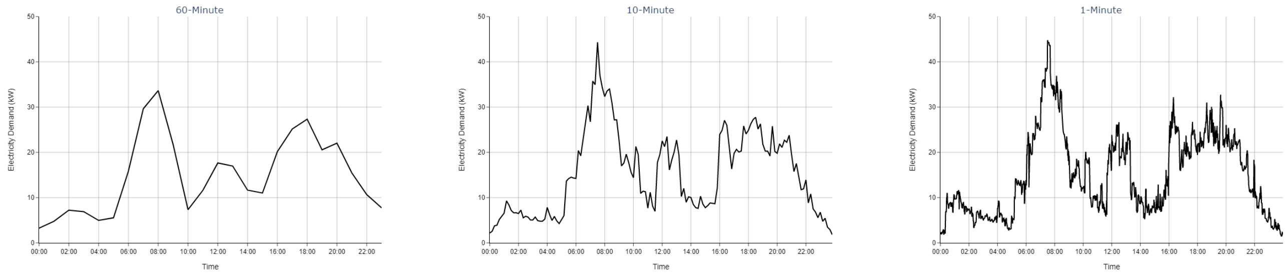
To allow the location to be assessed, markov chain probability data has been generated to determine the destination based on the start location. This has been differentiated by 6 time periods (00.00-07.00, 07.00-10.00, 10.00-13.00, 13.00-16.00, 16.00-18.00, 18.00-00.00), and separately for weekdays and weekends. This logic will allow future development of charging behaviour strategies when the factors determining whether a car is charged at home, at work or at a commercial charging location are more apparent.

Table 1 shows an example output for a day's car use. The 'Energy Demand Engine' module (see below) allows the charging behaviour, per-mile energy use, battery capacity and charger capacity to be defined. This allows the impact of variation in these factors on de-



(a) *60-min* (b) *10-min* (c) *1-min*

Figure 3: Demand profile at different time-average resolutions for a single house



(a) *60-min* (b) *10-min* (c) *1-min*

Figure 4: Demand profile at different time-average resolutions for 10 houses

mand patterns to be assessed against the same car usage.

Weather

Weather is a critical input for a number of elements within the overall model. Temperature affects building heat loss, heat pump COP and PV panel performance. Cloud cover, humidity and ozone can be used to determine PV output. Detailed weather data from a number of sources (Metar, Renewablesninja, Tomorrow.io, etc.) are used depending on location and specific model requirements.

Space heating requirements and renewables generation can vary significantly from year-to-year, therefore the ability to run multiple years is critical to assess potential performance variability.

Generation and Storage

Incorporating local electricity generation (typically using solar PV in a domestic context) and energy storage (typically battery or thermal storage) is increasingly common in both new-build and retrofitted properties. In the context of grid impact, generation and storage can be used to mitigate peak loads, particularly using optimisation controls.

Energy Demand Engine

The controllable and shiftable loads (heating and EV charging) are modelled within a sub-model that allows per-timestep intervention.

The ESRU developed model 'IDEAS' (Murphy, 2012) was primarily developed to assess specific control schemes on domestic heating but includes an single zone heating model that incorporates standard heat loss equations, fabric properties and use behaviours. The heat gains from the 'OccDem' model have been integrated with the building model to ensure consistency between occupancy, appliance use and heating demand.

The heating setpoint for the specific timestep and zone temperature for the previous timestep are used to determine the ideal heat input for the current timestep to meet the setpoint. This heat input can be modified to account for a surplus or shortfall in heat availability (i.e. grid restricted heat pump operation, excess renewable generation etc.).

For EV charging, the charge and location are determined at each timestep based on the use model. The model currently assumes that the vehicle will be charged at home unless below 20% of full charge while away from the home location. This logic will be updated as charging behaviour data becomes available to account for different behaviours and incentives (e.g. free or subsidised workplace charging).

Modelling Resolution

Identifying the peak loads on an electrical system using stochastic, bottom-up modelling of potential loads, requires a modelling resolution consistent with the input data and typical run times of individual demands. 'OccDem' has a 1-minute resolution, which is consistent with most power-intensive appliances (cooker/oven, kettle, microwave, shower) being typically run for at least 1 minute (Zimmermann et al., 2012). The modelling does not reflect transient power impacts, therefore a smaller timestep would be impractical. The model, however, has the flexibility to run a longer timesteps, with 30 to 60-minute demand-averaged steps typically used for annual demand analysis.

Figure 3 shows the impact of running the same house at a 1-, 10- and 60-minute resolution. Figure 4 shows the same results for a 10-house network. This highlights that capturing the demand peaks requires a 1-minute resolution, with absolute peak value information lost at 10-minute and very limited peak information at 60-minute resolutions.

Assessment Period

Analysis of full year results indicates that heating is the main driver of peak loading. Car use is largely non-seasonal and therefore any peaks associated with EV charging are as likely in the winter heating period than other periods. To reduce modelling time to allow for a 1-minute resolution basis, ADMD modelling is focused on the November to March period (217,440 timesteps).

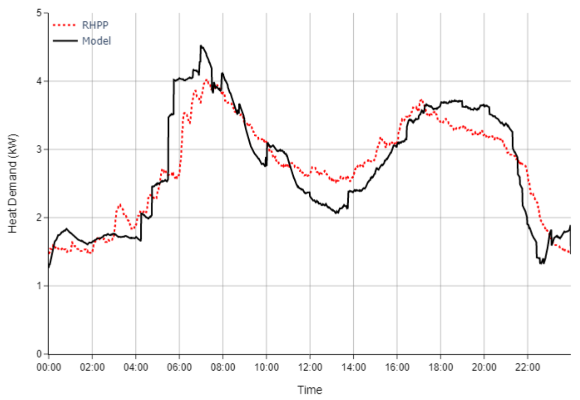


Figure 5: Average heat per household

Validation

Model calibration and validation will be an ongoing process as new behavioural data linked to domestic heat pump and EV charger use emerge.

For validation, 100 sets of 2-bedroom houses have been modelled with a mix of ages and a 80m2 floor area for comparison with the RHPP dataset. The RHPP is acknowledged as not being representative of UK housing (Love et al., 2017), with two-thirds being social housing against 17% as a proportion of UK housing, and as stated, a preponderance of 'always-on' heating. Without a detailed breakdown of the RHPP housing and household characteristics, the 100 houses were modelled broadly as per the average UK house.

Figure 5 shows the average heat pump heat output from the RHPP dataset for the Nov-Mar period, in comparison with the average for the 100 modelled houses with the demand normalised to the RHPP average to account for the uncertainty between modelled and RHPP populations. The results indicate that the timing and extent of both the morning and late afternoon peaks is consistent, indicating that the timing behaviour assumptions are broadly accurate.

The primary discrepancies are (1) a lower mid-afternoon demand, which may be consistent with a lower quality housing stock requiring higher heat input to maintain temperature and (2) a higher mid-to-late evening demand, which indicates that the timing of the heating switch-off may be earlier, on average, than currently assumed, or there is a tendency to reduce heating temperature in this period.

Overall, the model output shows a good correlation with the RHPP data given the uncertainty over the specific housing in the RHPP data.

The reduction in demand in late evening and the overall lower overnight demand level, when they high prevalance of always-on heating is considered, is only achieved if a reduction in temperature setpoint is assumed. In the model, this reduction is allowed to vary between 0-2°C from the daytime setpoint.

The car use model has been verified as statistically consistent with the NTS dataset. Further calibration and validation of the EV charging data is ongoing using the 'My Electric Avenue' dataset.

Case Study

To illustrate the primary applications for the developed model, the 100 sets of households modelled for the validation phase are used to consider a variety of potential ADMD related issues. The modelled houses have individual, stochastic occupancy, appliance, hot water, and EV use profiles, with the linked building fabric, and space heating and car charging behaviours allowed to vary for each model run.

The case study population is an extreme case where 100% heat pump (all air-source) and EV ownership is assumed, the results are therefore solely indicative of model potential not realistic near-term demand profiles.

Overall Results

Figure 6 shows the average electricity demand for each end use for the 100 modelled households in the Nov-Mar heating period. The morning demand peak is primarily driven by space heating, with the afternoon demand peak having a more mixed end-use balance, although heating remains predominant.

For the 100 households, the peak modelled demand was 411kW (compared to 91kW without heat pumps and EVs). This occured at 7.50am on Nov 19th, and was 79% heating demand, 15% appliance demand, 4%

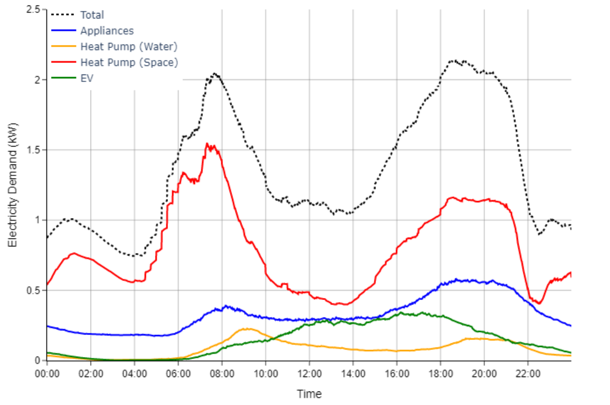


Figure 6: Average per-household end-use electricity demand for 100 representative households

#	Date	Time	Peak (kW)	Heat %	EV %
1	Nov. 10th	16.21	55.8	44.8	26.3
2	Nov. 20th	08.30	55.1	55.5	26.7
3	Nov. 19th	18.20	56.9	45.5	38.8
4	Nov. 19th	19.42	58.4	33.2	25.2
5	Dec. 26th	18.10	52.2	43.7	28.2
6	Nov. 16th	17.45	50.8	43.1	43.5
7	Nov. 19th	07.35	51.4	77.0	14.4
8	Feb. 28th	18.39	54.7	37.8	26.9
9	Nov. 19th	19.09	56.4	41.8	39.2
10	Nov. 29th	19.01	56.2	45.0	39.3

Table 2: Peak load timing and breakdown for each 10-house sub-group

hot water heating, 2% EV charging. Heating is the main driver for all highest load values. EV charging, even if opportunistic, is not a key driver to peak loading at this network scale based on the assumptions and modelled behaviours.

Table 2 shows the breakdown of the maximum demand for each 10-house sub-group in the dataset. At this network scale, the proportional heating contribution to the peak demand is significantly lower than the 100-household case, with a significantly greater influence from opportunistic EV charging. EV charging impact on peak loads is therefore likely to increase in significance with a decrease in network size.

At the individual house level, there is a high incidence of concurrent heating and opportunistic EV charging demand, often in the same period as peak appliance loads. This indicates a potential value in shifting heat demand via storage and overnight EV charging via timing controls, and tackling high individual household peak loads in parallel with overall feeder peaks.

Impact of heating behaviours and fabric performance

As outlined above, the RHPP dataset for heat pump households shows a significantly greater prevalance

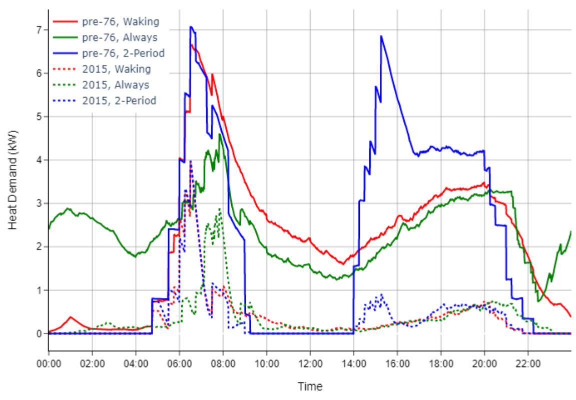


Figure 7: Average total 10-house heating demand for different heating patterns and building fabric performance

Building Standard	**Heat Behaviour**	**HP** (kWe)	**HP** %	**Total** kWe
Pre-76	Waking	48.5	100	59.0
Pre-76	Always	43.3	100	52.5
Pre-76	2-Period	43.9	100	64.6
2015	Waking	34.5	80	45.6
2015	Always	30.2	70	47.4
2015	2-Period	33.6	72.5	44.2

Table 3: Total peak load variation for different building fabric and heating behaviours for 10 houses

of 'always-on' and 'waking hours' heating patterns (see Figure 2). Further data is required, particularly for heat pumps installed in newer housing with significantly better thermal performance. More typical heating patterns associated with gas boilers, i.e. behaviours typical where the system is not heat output or temperature limited, may predominate.

Figure 7 shows the average for a 10-house group of Nov-Mar heating patterns for different behaviours ('Waking', 'Always' and '2-Period') and building fabric standards (pre-76 (with standard upgrades) and 2015), with significant variation and potential impact on ADMD level. The older 'pre-76' housing shows significant variation in the peak average demand, with the '2-Period' behaviour resulting in the highest value. For the new-build '2015' housing, there is limited variation as the much lower heat loss means the daytime setpoint is reached quickly during the morning peak period and maintained with only minor heat input.

Table 3 shows the peak heat pump and total electricity demand, plus the percentage of heat pump capacity in use at the peak period, for the six behaviour and fabric cases. The is more variability with behaviour in the older housing, with significant instances of 100% heat pump use seen. This is important for assessing ADMD in areas with different levels of building thermal performance.

Impact of EV charging and charging behaviours

EV charging, particular with the assumed higher power 7.36kW chargers, have the potential to add a significant additional load at the individual house level. However, in comparison with heating, the frequency and timing of at-home charging is less predictable.

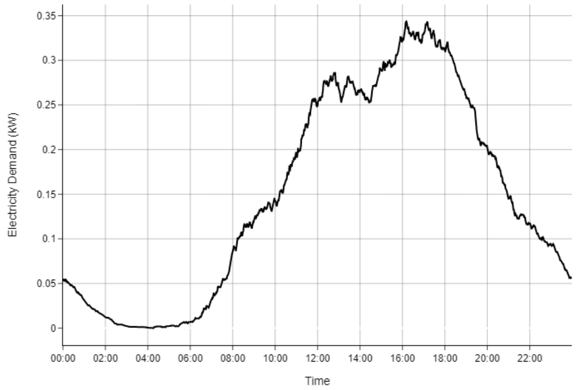


Figure 8: Average per-house EV charging power for 100 households

Modern EVs have a typical range of 140-280 miles with a 40-80kWh battery. The average daily journey distance from the NTS data is 24.2 miles, therefore the majority of cars could either manage several days between charging or only require a small daily top-up charge to maintain a full battery.

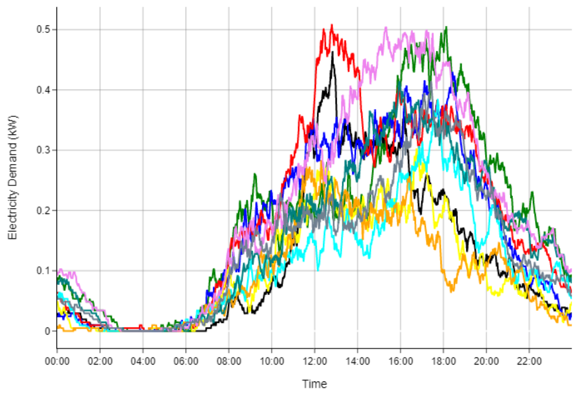


Figure 9: Average EV charging power per 10 household groups

The base model assumes opportunistic charging (i.e. the car is charged immediately on return). The average per-house demand for the 100 modelled houses shows a peak in the 4-6pm period (see Figure 8), which is consistent with typical 'rush-hour' pattern of returning home from work or other external activities in this period. This would also place EV charging peaks in the same period as the late afternoon appliance and heating peaks.

Within the average charging data is significant variation per household and per smaller groupings. At the 10-house level, Figure 9 shows significant timing and average power variation in comparison with the 100-house average profile. Figure 10 shows the per-household variation for one of the 10-house sub-groupings, indicating a wide range of charging patterns are possible at this resolution.

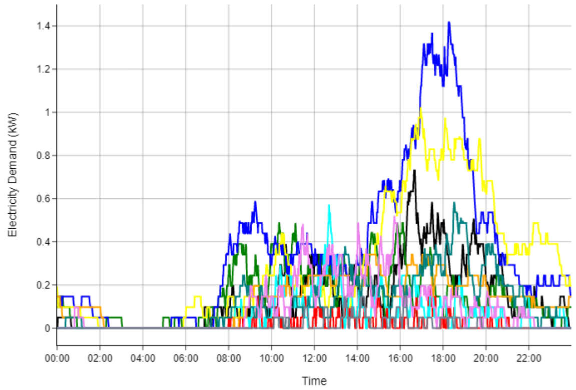


Figure 10: Average EV charging power per household within a 10-house sub-group

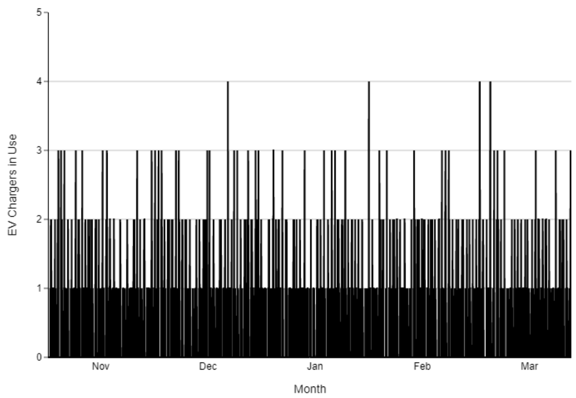


Figure 11: 1-minute total charging profile for a 10-house sub-group

At the network feeder level, the diversity implications of either opportunistic or forced EV charging timing needs to be understood. For the 10 10-house sub-groupings, over the 5-month modelling period, for 9 of the groupings, the maximum concurrent use is 4 chargers, with 3 for the 10th grouping. A example 5-month at 1-minute profile for one of the groupings is shown in Figure 11, which indicates that the 4 charger-in-use cases are relatively common at this scale. At the 100 household scale, 15 was the maximum concurrent use (see Figure 12).

Time-of-use tariffs are the current principal means to force charging away from the peak total demand periods. Care, however, need to be taken to ensure that this does not result in significant peaks if the same cheaper charging periods are common. Taking at extreme case with all households having a low-cost charging tariff starting at 1am and 100% overnight charging behaviours, Figure 13 shows the potential impact on total electricity demand for a 10-house sub-group. This would indicate that, even if this be-

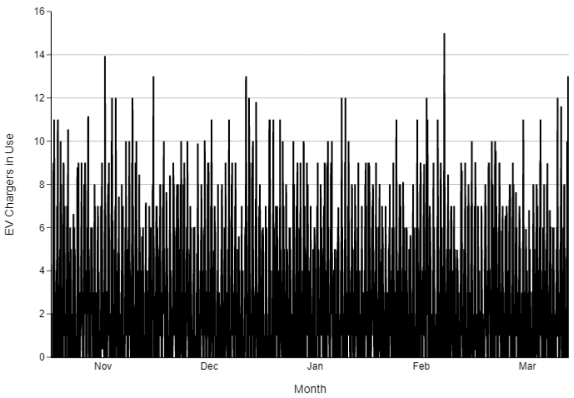


Figure 12: 1-minute total charging profile for the 100 modelled households

haviour was only partially prevalant, the impact on peak charging in specific periods could be significant.

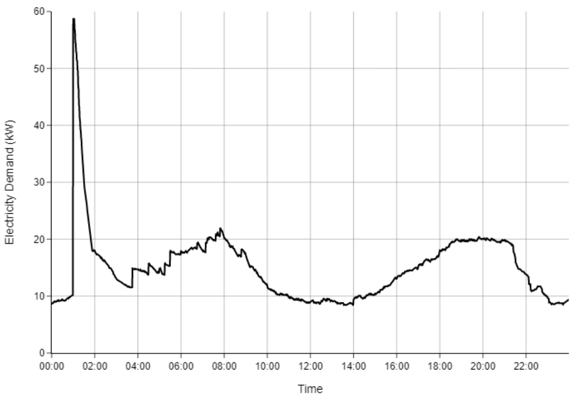


Figure 13: Average total electricity demand for a 10-house sub-group with a low-cost EV charging period from 1am

Discussion / Future Work

The current model basis assumes no alteration to occupant behaviours or optimisation controls based on tariff variations, and energy generation and storage utilisation. The probability models in the appliance and hot water demand models can be easily adjusted to reflect different forcing mechanisms. Moving horizon optimisation is currently being implemented within the model to allow both control of individual household demand and across multiple households in communal schemes.

Conclusion

The current progress of model development has demonstrated that 1-minute resolution stochastic modelling of the impact of heat pump and EV charging is both necessary and viable. Comprehensive datasets for calibration and validation in a UK-context are rare. While this makes calibration challenging, it does highlight the need for accurate modelling to understand the impact of behaviours and forcing mechanisms as long-term monitoring is difficult to implement.

The initial results would indicate that the impact of heat pumps and EV will vary with the network scale. The impact of EV charging on peak loads being proportionally higher in smaller networks based on the assumption of a high likelihood of at-home charging and cars being charged when available. Significant work is required to understand to what extent heating system operation is modified from typical boiler use patterns, and whether the tendency for more 'always-on' heating in the RHPP dataset used was typica or anomalous. However, the bottom-up approach and the extensive use of easily modified probability modules within the model should ensure that the model provides a platform for future research in this area.

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