Towards bottom-up modelling of the electricity demand of Huntly in 2030

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Abstract

The Scottish Government has committed to a Just Transition to net-zero greenhouse gas emissions in Scotland by 2045. This is expected to lead to an increase in electrical loads from domestic heating and Electric Vehicle charging. The Cloud ZUoS project aims to demonstrate a platform to support optimisation of electricity costs within a local system. The platform will monitor the energy use of domestic properties and light industrial sites in Huntly, Aberdeenshire, and control the primary electrical loads in participating properties. This paper uses white-box modelling tools to infer simplified grey-box building models to create a bottom-up electricity distribution network model. A simulation architecture is presented which incorporates simplified models of building demand into a network simulation. The building model captures behaviour of key devices such as electric heating, microgeneration, behind-the-meter batteries and electric vehicle charging. The architecture supports the simulation of complex device control strategies which take inputs from the electrical network. The initial work on model evaluation, and the results of network simulations with uncoordinated device control and time-of-use strategies are presented.

Introduction

As part of the Scottish Government commitment to zero carbon by 2045, heat and transport have been identified as major targets for decarbonisation (Just Transition Scotland, 2020) in response to Climate Change advice (Committee on Climate Change, 2019). A Scottish and Southern Energy Networks (SSEN) report (Maltby and Mayo, 2019) notes regional differences to the rest of GB that give northern Scotland a unique opportunity to help Scotland accelerate the transition, with increased electrification to take advantage of Scottish renewable generation.

The Cloud ZUoS project is supported through funding from The Department for Business, Energy & Industrial Strategy (BEIS) via the Power Forward Challenge. The ZUoS vision is to enable the low-carbon transition, going beyond individual participants into the community by optimising energy use at a local level to increase the amount of Distributed Energy Resources (DERs), such as renewable embedded generation, heat pumps and EV charge points, which can be connected within existing distribution infrastructure capacity constraints. This will be achieved through the ZUoS platform, providing local system control to balance the local network with the project making recommendations for the regulatory change and required financial levers to make it possible. The platform will be deployed in a live pilot in Huntly, Aberdeenshire over the winter 2020 - 2021. The pilot will entail demonstration of control and will result in data for model development and verification through monitoring of DER operation and building demand.

Similar projects include Northern Isles New Energy Solutions (NINES) (SSEN, 2019) and 4D Heat (Myers et al., 2020). The former aims to create a smart grid in Shetland which will involve domestic heaters and a large-scale battery to maximise utilisation of wind generation, the latter aims to match electrical heat demand with national wind generation. Project Local Energy Oxfordshire (LEO) involves designing a platform where prosumers sell both energy and services (Darby and Banks, 2020), for example using peer-to-peer technologies.

This paper sets out a simulation framework for smart local energy networks in which models for forecast and control can be set. The modelling approach is bottom-up. The initial survey data for the Huntly pilot is used to select building archetypes and provide parameters for DERs reflective of the study area. The line data from SSEN's geographic information system (GIS) is incorporated into a network model. Through the use of co-simulation, the control of DERs is manipulated, to reflect real-world control. Current and future demand scenarios are presented, as well as two naive constraint mitigation control strategies. The power flow simulation yields data for evaluation of network power flows against equipment limits, voltage variability experienced at properties, and the extent to which householder comfort limits are met.

The project intends to utilise the simulation framework to model different future energy scenarios and regulatory environments in order to investigate the efficacy of different control strategies such as constrained scheduling (Kirli and Kiprakis, 2020; Unigwe et al., 2019). As well as scenario modelling, the models and simulation will be used in the live platform to forecast power flows up to 24 hours ahead, identifying constraints and actions to avoid them by influencing the operation of multiple DER types, feeding the forecast response back into the simulation. Such forecasting has been demonstrated using machine learning techniques (Antonopoulos et al., 2020).

Methodology

The electrical demand in Huntly in 2030 can be inferred by augmenting a model demonstrating existing demand with the expected additional large electrical loads as forecast by National Grid ESO and Scottish and Southern Electricity Networks. In this paper, only the expected additional large electrical loads are considered, i.e. the changing usage of small power devices is outside the scope of this paper.

Demand is distributed throughout a simulated electrical network, with power distribution system simulation and analysis performed in the software, GridLAB-D, (Chassin et al., 2008). Control models for certain loads are implemented in the Python programming language with co-simulation between the Python models and GridLAB-D implemented using HELICS, (Grid Modernization Laboratory Consortium, 2017).

Modelling Framework

The distribution system modelling is conducted across a range of test cases that are simulated across the course of a year. Each scenario has a fully specified definition, which includes network data, a list of connected DER assets, building thermal parameters, local weather data and user preference schedules as shown in Figure 1. The scenarios are described in the Simulation Scenarios section below; Scenarios 1-3 operate with device control according to in-built GridLAB-D models, which allows devices to operate based on the user preferences and device status (e.g. battery state-of-charge). Scenario 4 goes beyond this by implementing a control algorithm in Python which is used in a co-simulation with the GridLAB-D power flow solver. Device control may still operate according to user preferences or the DER asset status, however, this can be overridden, curtailed, or capped by an external controller, as shown in Figure 1.

House Load

Domestic electrical demand is modelled by the combination of a baseline demand model (for small power devices) by the University of Twente (Hoogsteen et al., 2016) and the demand due to assets modelled individually. These asset models are created for the additional loads so that they can reflect changes in environmental conditions, user behaviour and to allow testing and development of various control strategies. Commercial and industrial demand models are not included due to the geographic area selected.

Table 1: Load profile archetypes

Family Type	No. of household
Single Adult, no children	34
Single Adult with children	5
Couple, no children	20
Couple with children	14
Retired single	3
Retired couple	8
Total	**84**

The electricity loads are modelled in detail for this paper where the EV charging and electric heating are larger than other loads such as white goods and lighting. In order to concentrate on the modelling of the large loads, which contribute most to the expected demand change forecast for 2030, the smaller loads are represented by the aggregated load model. The Twente model includes plug loads and kitchen appliances commonly found in households in the UK . It uses a probabilistic behavioural simulation to generate static load profiles across six different household archetypes. Huntly demographic data from (Aberdeenshire Council, 2019) is used to assign each property in the model to one of these archetypes as shown in Table 1. Household power consumption is the sum of demand determined by the Twente model and electrical load from any DER assets modelled individually.

Local Network Model

The electricity distribution network is the backbone of the simulation. The local DNO, SSEN, provided local network data of the 400V, 11kV and 33kV network. This data is sufficient to create a power flow model of the network from the primary substation, serving the whole of Huntly, down to the individual supplies to each property. This line data was provided as part of a GIS map.

A network diagram of the simulated section of the low voltage network is shown in Figure 2. Multiple pilot participants are connected to this section and there are no commercial properties.

Asset Placement

With survey work for the pilot yet to be completed, this study uses the following rules to add assets to the network with details in the appropriate section:

- Existing PV is added from satellite imagery
- EV chargepoints are added to houses which have suitable outside space (e.g., private driveway) or participants are interested in installing them.
- Heat pumps are added where participants have expressed interest in installing them.
- Batteries are added where there are PV systems and where participants are interested in installing them.

In all but Scenario 1, there are more available locations to place assets than the number of assets to be

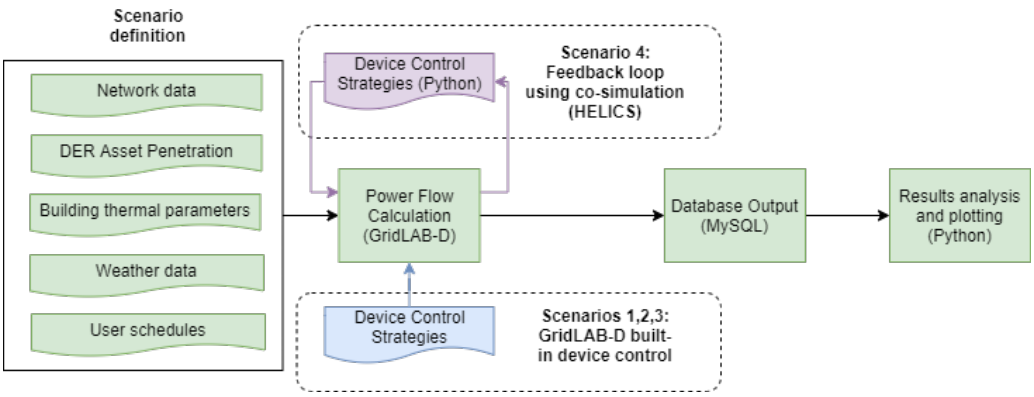


Figure 1: Simulation architecture

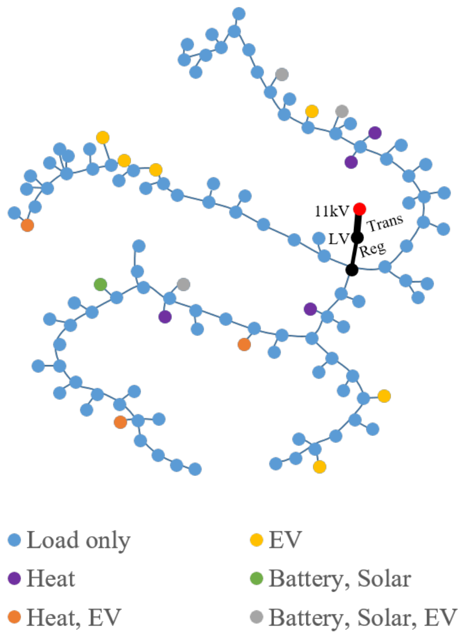


Figure 2: Network diagram of the LV section simulated.

placed. For these cases, assets are distributed across a random subset of the list of suitable houses. Figure 2 indicates the resulting locations of assets.

Building Heat Model

The building heat models use the built-in house object in GridLAB-D. The model uses a lumped capacitance (2R2C) which is a grey-box model for heat flow. The parameters for these models are derived from white-box building models created in the specialised heat-flow model ESP-r, by the University of Strathclyde, detailed in Krawczyk (2020). Two building heat models of a bungalow and a detached house are used in scenarios where a heat pump is simulated. The geometries of the two models are shown in Figure 4. The input parameters for the archetypes are summarised in Table 2. The parameters are used by GridLAB-D to create a suitable 2R2C model, represented in Figure 3. The equivalent thermal parameters are derived from the input values according to equations 1 to 4 based on Pacific Northwest National Laboratory (2012).

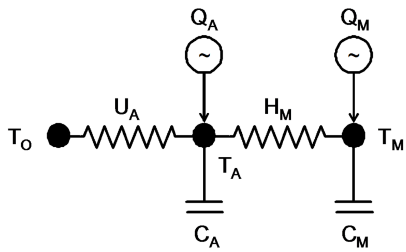


Figure 3: Equivalent Thermal Parameter Model implemented in GridLAB-D

The total heat loss coefficient (conductance), U_A, is calculated as:

$$U_A = C_{p,air} V_{air} I_{air} + \sum_{i=1}^{n} \frac{A_n}{R_n} \quad (1)$$

where $C_{p,air}$ is the volumetric heat capacity of air; V_{air} is the interior air volume; I_{air} is the air infiltration rate; and A_n and R_n are the surface area and thermal resistance per unit area of building surface n, respectively.

The interior mass surface conductance, H_m, is calculated as:

$$H_m = h_s \times (A_{EW} + A_{IW} + A_C) \quad (2)$$

where h_s is the interior surface heat transfer coefficient; A_{EW} is the external wall area; A_{IW} is the internal wall area and A_C is the ceiling area.

The total air mass, C_a is calculated as:

$$C_a = 3 \times C_{p,air} \times (V_{air}) \quad (3)$$

The total thermal mass, C_m, is calculated as:

$$C_m = m_f \times A_{floor} - (2 \times C_{p,air} V_{air}) \quad (4)$$

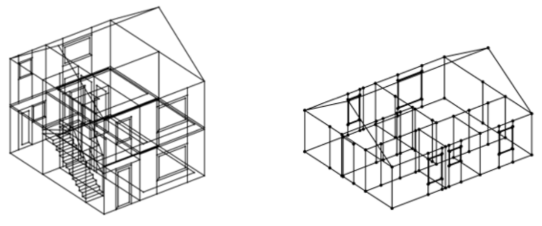
where A_{floor} is the floor area and m_f is the total thermal mass, per unit floor area.

Heat Pumps

Heat pumps are implemented in, and sized according to, the two different archetypes, and are programmed

Table 2: Key GridLAB-D House Model Parameters

Parameter (Unit)	Detached	Bungalow
Floor Area (m^2)	106.8	106.9
Wall Area (m^2)	95.3	77.9
Ceiling Height (m)	7.5	4.4
No. of Stories	3	2
R roof (m^2K/W)	2.3	2.3
R wall ($m^2K.W$)	2.3	2.7
R floor (m^2K/W)	1.5	1.4
R windows (m^2K/W)	0.4	0.4



(a) Detached archetype *(b) Bungalow archetype*

Figure 4: Geometries for building heat models

to operate whenever the modelled indoor temperature is lower than the temperature setpoint (i.e. consumer heating schedule). The heat pump operates at its maximum rated power when the modelled house temperature is below the current set point. They are sized suitably to maintain the set temperatures throughout the year. The detached house archetype has a heat pump size of 11 kW (electrical) and the Bungalow archetype has a heat pump size of 7 kW (electrical). Both heat pumps operate with a varying coefficient of performance (COP) depending on the differential between the outside and inside temperature, with the COP decreasing as the differential decreases (Pacific Northwest National Laboratory, 2012).

Solar PV

The GridLAB-D model for PV installations calculates the solar PV output from solar irradiance, a metric provided by local weather data. The model is combined with a separate inverter model. The conversion from DC to AC, and the corresponding losses, are modelled within GridLAB-D.

Battery

Battery operation is modelled by combining the built-in battery and inverter models of GridLAB-D. The battery energy storage model captures the power flows during charging and discharging of the battery. The inverter model implements the control of the battery. For this paper, the inverter control strategy is to maximise self-consumption (i.e. charging instead of exporting energy, and discharging instead of importing energy), whilst avoiding excessive switching between charge and discharge states, to avoid an unnecessary reduction in battery lifetime. For this purpose, the four quadrant control method, specifically dedicated for batteries, is used. Within this model four following power thresholds, shown in ascending order, were assumed: charge on threshold (-0.05 kW), charge off threshold (0 kW), discharge off threshold (0.05 kW) and discharge on threshold (0.1 kW).

Table 3: EV charger deterministic model specifications

Parameter (Units)	Value
Charging efficiency (%)	0.9
Battery size (kWh)	22
Maximum charge rate (kW)	7.3
Mileage efficiency (miles/kWh)	3.8
Std dev. of schedule times (s)	300
Std dev. of distance variation (miles)	2.0

Electric Vehicles

The charging behaviour of the electric vehicle (EV) charge points are modelled using the deterministic EV charger class in GridLAB-D. Their specifications are shown in Table 3. The charging behaviour of the EVs is determined by the user preference, as discussed in the simulation scenario section. However, the amount of charge required, and the plug-in time vary according to a normal distribution, with the standard deviation of distance travelled per day, and plug-in times shown in Table 3.

Weather Data

The simulation uses historic weather data from a typical meteorological year (TMY). The weather data used is based on measurements from the weather station at Aberdeen Dyce between 2004 and 2018 formatted by Lawrie and Crawley (2019). The weather data input parameters are: temperature; humidity; direct and diffuse solar irradiance; wind speed; and rainfall.

Simulation Scenarios

There are four key scenarios:

1. Baseline model (2020)
2. Future demand with baseline control (2032)
3. Future demand with peak hour avoidance (2032)
4. Future demand with network aware control (2032)

Scenario 1 has a DER penetration representative of Huntly today. Scenarios 2-4 have DER penetrations representative of Huntly in 2032.

Asset Penetration Levels

This paper intentionally focuses on future energy scenarios from the 2030s. The choice of 2032 is aligned with SSEN's Distribution Future Energy Scenario (Maltby and Mayo, 2019), which bases its estimates on the NGESO Future Energy Scenarios (National Grid, 2019) and outlines the expected future DER

Table 4: Asset count for simulation scenarios

Scenario	Heat Pumps	EVs	PV & Batteries
1	0 (0%)	0 (0%)	0 (0%)
2,3,4	7 (8.5%)	12 (14.3%)	4 (4.8%)

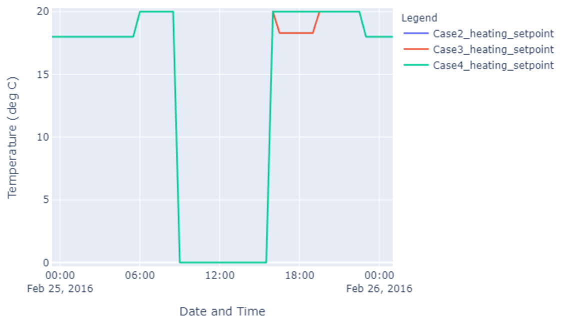


Figure 5: Heating set points for all scenarios (Note: Scenarios 2 and 4 are identical)

penetration for their network area. The scenario applied here is based on 'steady progression' estimates with asset counts for the simulation shown in Table 4.

Control Strategies

The control strategies for Scenarios 1 and 2 are the same. These are based on business-as-usual control whereby devices act to benefit the device owner, without consideration for the rest of the distribution network. The control for each scenario is detailed below. Scenario 1 has no DER assets connected, therefore no device control is specified. In Scenarios 2-4, the batteries connected to the network operate to maximise self consumption, as is typical for many domestic PV battery systems in the UK, and this is not modified in any Scenario.
The following control is used for each asset in **Scenario 2**.

- Heat Pumps: follows a typical domestic demand schedule, as shown in Figure 5, with a morning and evening peak.
- Electric Vehicles: as soon as a vehicle is plugged in, it will immediately charge until full, or the consumer unplugs this. The electric vehicles used are described in the methodology section. The user schedules are based on a sample dataset built into GridLAB-D as shown in Table 5.

The following control is used for each asset in **Scenario 3**.

Table 5: EV default charging windows from Bureau of Transportation Statistics (2003)

Arrival from work	Leave for work	% of EVs using this schedule
14:25	05:25	33%
17:20	05:30	33%
05:27	20:47	33%

- Heat Pumps: follow a typical domestic demand schedule, but with a drop in temperature of 1.7 °C within DNO 'red rate' periods as shown in Figure 5, following the comfort aware approach (Marche et al., 2017). 'Red rate' periods are when Distribution Use of System (DUoS) charges for half-hourly metered customers are highest and are an indication of when the distribution network is most heavily loaded. For 2020, these times are 16:30-19:30 weekdays (SSEN, 2020).
- Electric Vehicles: consumer behaviour continues as in Scenario 1, however EVs only charge outside DNO 'red rates'.

Scenario 4 uses co-simulation, as shown in Figure 1, this allows for the simulation to be queried and modified whilst it is running. The control implemented for this scenario is intended to prove the capability of co-simulation. Algorithm 1 shows the control which is applied every 30-minute interval to the GridLAB-D simulation. The curtailment for both EVs and heat pumps operates to limit power for both devices. This curtailment is applied when any LV mains cable loading exceeds 90% of its maximum current rating; the limit is then removed if all LV mains cables are loaded less than 80%. If there is no limit, both devices operate as they would in **Scenario 2**. Currently, this algorithm is applied to all EVs and heatpumps. However, the platform is capable of applying a rotational neighbourhood participation scheme similar to Unigwe et al. (2019). Additionally, the objective of the control can be multiple as demonstrated by Kirli and Kiprakis (2020) using scheduling techniques such as particle swarm optimisation. Objective criteria may include green house gas emissions, voltage variation and economic benefit (Wu et al., 2017).

```
connect to GridLAB-D federate;
connect to Python controller federate;
for every 30 minutes in simulation year do
    for all LV mains cables do
        check current magnitude;
    end
    if any cable is overloaded then
        curtailment rate = overload percentage;
        curtail all EV charging;
        curtail all heat pump usage;
    else
        maintain all EV charging;
        maintain all heat pump usage;
    end
end
```

Algorithm 1: Control implemented via HELICS co-simulation

Discussion of Results

The simulation framework within this paper allows for direct comparison of control and DER penetration

Table 6: Summary of line losses

Scenario	Max Power Loss (kW)	Annual Energy Loss (MWh)
1	0.96	0.62
2	9.57	17.62
3	10.07	17.90
4	11.49	15.90

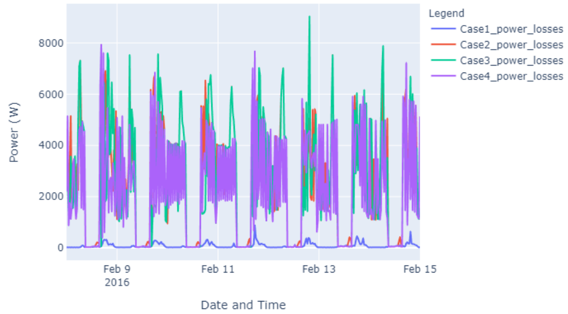


Figure 6: Active power loss on the network across all Scenarios

scenarios. The results below are shown for all four scenarios, and how the control of assets impacts the relative network conditions, carbon emissions, and user requirements.

Model Runtime

Scenario 4 (with co-simulation) is interrupted every 30 minutes and hence, it takes more than 20 times longer to run in comparison to Scenarios 1-3. This runtime is further tripled if the interruption interval is reduced to 5 minutes. Interrupting the simulations more frequently allows for more fine-grain control over assets (i.e. curtailment occurs within a more precise time window).

Line Losses

Active power line losses for the entire LV network are presented in Figure 6. The highest instantaneous power loss, and cumulative annual energy loss for each scenario is shown in Table 6. A key result is that Scenario 4 reduces annual energy loss, since devices are intentionally operated outside high network loading conditions.

Network Voltages

The areas of the network with the greatest power loss are used to assess the voltage drop. The LV main line with highest voltage drop on phase B was found to be 'F2_M2S'. This line supplies electricity to 4 heat pumps (3 on phase B) and 3 EV (2 on phase B). The voltage experienced by a user at the end of the LV main is assessed at the point in time when main line phase B loading is maximum for Scenario 1 (i.e. 6pm on the 22nd of November). The resulting line voltage drop is presented in Figure 7. Avoiding the peak hours introduced in Scenario 3 causes a significant voltage drop (to 0.9204 p.u.), resulting in the voltage below statutory limits (-6%). This is caused because lowering the set temperature by 1.7 °C was not enough to avoid heat pumps turning on during the peak period. Network aware control in Scenario 4 significantly reduced the voltage drop on the first 15 network points while the last two points have similar voltages to Scenario 2. Such results show that this control algorithm can be valuable when for reducing line voltage drop. As a naive control objective, line loading was chosen. It is noted that voltage variations are also an important constraint in LV networks (Vovos et al., 2007).

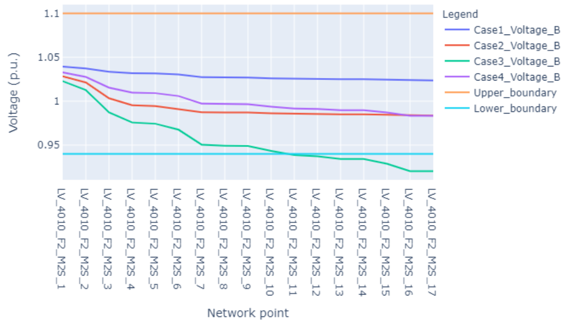


Figure 7: Voltage drop along a three phase LV main at the time of the highest power loss across all scenarios

Secondary Substation Transformer Loading

The future load scenarios show a significant increase in peak time loads. The apparent power loads for all cases in the week of the year with the highest peak load for Scenario 1 were compared with the transformer ratings. The results of the comparison are presented in Figure 8. It is noted that the transformer loading in future scenarios does not exceed its rating at any simulated time step. Avoiding the 'red rate' periods introduced in Scenario 3 postponed the peak, but at some stages the 1.7 °C drop in the house temperature set-point was not enough to avoid heat pump loads at later stages of the afternoon peak hours. In case of the Scenario 4, the load is not only shifted from the 'red rate' periods but also the high transformer loading occurring during the morning peak is also reduced compared to Scenarios 2 and 3.

Cable Loading

In order to assess the effectiveness of Scenario 4 in reducing line and cable loading, the worst case loading from Scenario 2 is presented and compared with Scenarios 3 and 4 in Figure 9. Currents higher than line ratings occur in all future load scenarios. It should be noted that simple control introduced in Scenario 3 avoids some of the current spikes from Scenario 2, but causes new (increased) overloading at later times. A responsive approach is introduced in Scenario 4, which is able to lower the current level below the threshold every time the cables became overloaded.

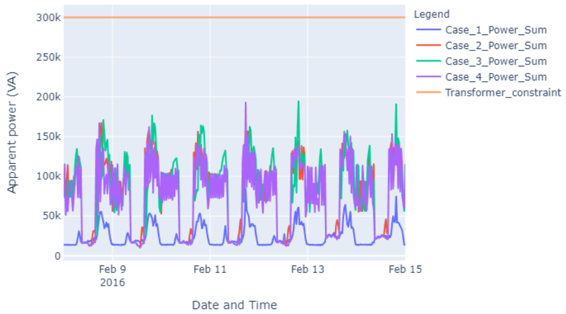


Figure 8: Transformer loading across all scenarios

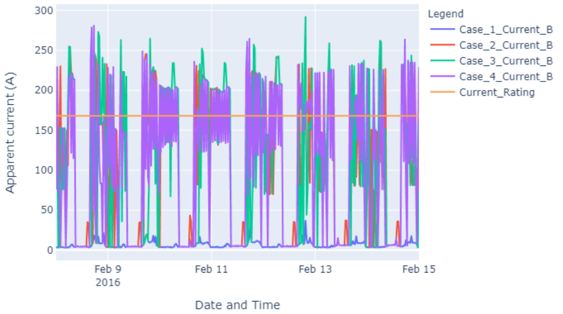


Figure 9: Underground cable loading for all scenarios

However, in the half-hour after curtailment is applied to reduce the demand, the network is not overloaded, and demand is allowed to go back to a normal level. This results in an undesired oscillating demand profile, as shown in Figure 9.

Household Heating

The managed interior air temperature is compared with the user preference set points in order to express the level of comfort as shown in equation 5, (Marche et al., 2017). The function (b_{mt}) in equation 5, quantifies the thermal comfort using a Gaussian function. The comfort level is inversely proportional to the difference between the mean preferred indoor temperature $\overline{T}_{pref}$ and managed indoor temperature T_{mt}. The variance in preferred temperature ($\sigma^{T_{pref}}$) is also accounted for.

$$b_{mt} = exp\left(-\frac{(T_{mt} - \overline{T}_{pref})^2}{2(\sigma^{T_{pref}})^2}\right) \tag{5}$$

Evaluation of the comfort levels using equation 5 shows in a 4% lower comfort level in Scenario 4 in comparison to Scenario 3. This is confirmed by the lower mean temperature of 16.96 °C while it is 17.15 °C in Scenario 3. Throughout the whole year of simulations, the indoor air temperature falls below the preferred temperature only 1.94% and 4.24% of the time for Scenario 3 and 4, respectively.Scenario 2 meets the preferred temperature for every time period simulated.

Although heating in Scenario 3 is curtailed throughout the peak ‘red rate’ periods, it is still able to come on if the indoor temperature drops below the preferred temperature. As such, the preferred temperature is only not met, when the home is being ‘re-heated’ from a temperature dip.

Scenario 4 attempts to avoid line overloading, however, it oscillates the heat pumps off and on, this meaning that heating preferences are not always met since heat pumps may be curtailed, when they require to be on at full power.

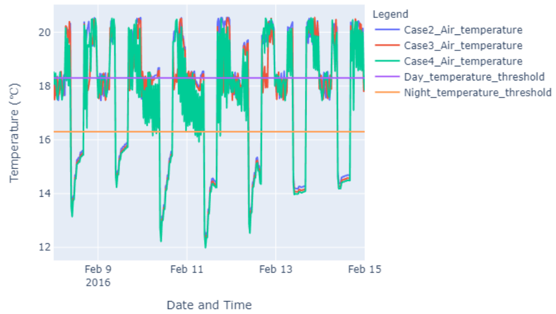


Figure 10: Comparison of interior air temperatures in Scenarios 2, 3, and 4.

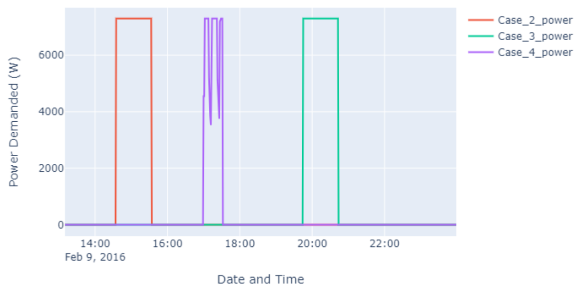


Figure 11: Power demand for a representative house with an EV across all scenarios

EV Charging

In order to assess if the EV charging control in any of the scenarios is detrimental to the user experience, a comparison is carried out to assess the number of times in a year that the desired state-of-charge for the electric vehicles on the network are not met.

The simplifying assumption is that all EV users require 100% SOC for their journey to work on weekdays, and SOC during other times is not important to them. The analysis checking if the desired SOC was fulfilled for all EV users is carried out on the results. This analysis shows that all EV charging needs are met for entire year of simulation.

Figure 11 shows that different scenarios result in different charging times. For example, Scenario 1 charges as soon as the EV is plugged in (at 17:00), Scenario 3 delays charging until after peak times, and Scenario 4 operates with curtailed charging at around 66% curtailment - indicating that the line was loaded

Table 7: Carbon Emissions for electricity use over one year

Scenario	Energy Usage (MWh)	Carbon Emission (tCO_2)
1	201	62
2	548	170
3	542	168
4	506	157

66% above the upper limit.
User needs are met in Scenarios 3 and 4 due to the large period of time available for charging ($>$ 12 hours in every scenario). The charging rate is set at 7.3 kW, meaning a full charge can be completed in just over 3 hours, although 7 kW chargers are increasingly common, 3 kW chargers continue to be deployed. Interrupting the less powerful chargers may result in user needs going unmet.

CO_2 Emissions Savings

The difference in carbon emissions between the scenarios can be compared by using National Grid Carbon Intensity Data (National Grid ESO, 2020b) alongside half hourly energy usage at the substation level. National data from 2016 is used in the comparison, to match the simulation year. The results are shown in Table 7.
The carbon intensity of peak hours (DNO 'red rates') is calculated as 326 gCO_2/kWh which compares to 299 gCO_2/kWh for all half hours in 2016.
It is expected that the increasing penetration of heat pumps and EVs on the electricity network will increase the energy demanded, as shown. Scenarios 2 an 3 have approximately the same energy consumption, however, Scenario 3 reduces carbon emissions versus scenario 2 by reducing network losses and carbon emissions, which are both highest at peak times. Scenario 4 brings about the most significant carbon savings, and minimum energy usage, however, this is partly due to curtailment, which results some heating requirements not being met.

Limitations of Approach

A half-hourly data inspection and network control interval was used in order to simulate a year of operation with a process time of less than a day, with GridLAB-D handling the sub half-hour operation internally. Inspection and control operating at a higher resolution (e.g. minutely) would assist in confirming correct operation of the models.
It is also noted that, the configuration of the 2R2C heat models for each house is carried out using GridLAB-D's built in tool to convert survey parameters to model parameters, results in buildings being created with low thermal inertia. However, direct input of the model parameters would more easily support the alignment of models with archetypes or pilot data.

Conclusions

A framework has been demonstrated to incorporate bottom-up models of domestic buildings and DERs. Four energy scenarios have been simulated with different control strategies to mitigate constraints. Performance of the strategies are assessed according to: changes in power profile and peak power flow; consumer comfort; and, CO_2 emissions. These early results indicate that LV network constraints can occur with the Steady Progression future demand scenario. Assessment of the modelling approach will be possible by comparison with sources of data that will be available to the project: live telemetry data from the pilot; and, Energy Systems Catapult data from their Living Labs and their Consumer Vehicles and Energy Integration project. One complication that will arise is the impact of COVID-19 on GB consumption patterns, as raised by (National Grid ESO, 2020a). Typical demand profiles and historical demand data may not be representative of demands and device operation during the period of the Cloud ZUoS trial.
In order that the framework can be used in a future live service, additional models are required for behind-the-meter battery systems and hot water heating and storage. In addition, some domestic battery controllers optimise charge and discharge cycles based on day-ahead electricity prices. For offline simulations, this optimisation will be replicated. The areas represented will be extended to include all the pilot areas in Huntly which will require models for small commercial premises. Constraint-based control can be enhanced to include voltage quality and violations.

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