Electricity Distribution

Vulnerability and Energy Networks, Identification and Consumption Evaluation (VENICE)

Webinar

30th August 2023

nationalgrid

Outline

1 Overview of Project VENICE

2 COVID19 Persistence Assessment

3 Cost of Living Crisis Analysis

4 Smart Meter Data and Vulnerability Research

5 Community Energy Engagement and Net Zero

6 Q&A

VENICE – project overview

VENICE is an NIA funded project that aimed to:

- Assess the impact of the pandemic and cost of living crisis on energy networks
- Explore and understand a range of vulnerability characterises
- Identify a novel ways of using smart meter data for vulnerability detection
- Provide guidance and support to local energy groups in their Net Zero journey

Delivery timeframe: July 2021 – August 2023

In collaboration with:

Electricity Distribution

Pandemic Persistence Assessment and Cost of Living Crisis Analysis

Callum Cheshire
Frontier Economics

nationalgrid

We used household-level smart meter data to investigate the impact of…

…the pandemic on electricity consumption…

…the pandemic on EV usage…

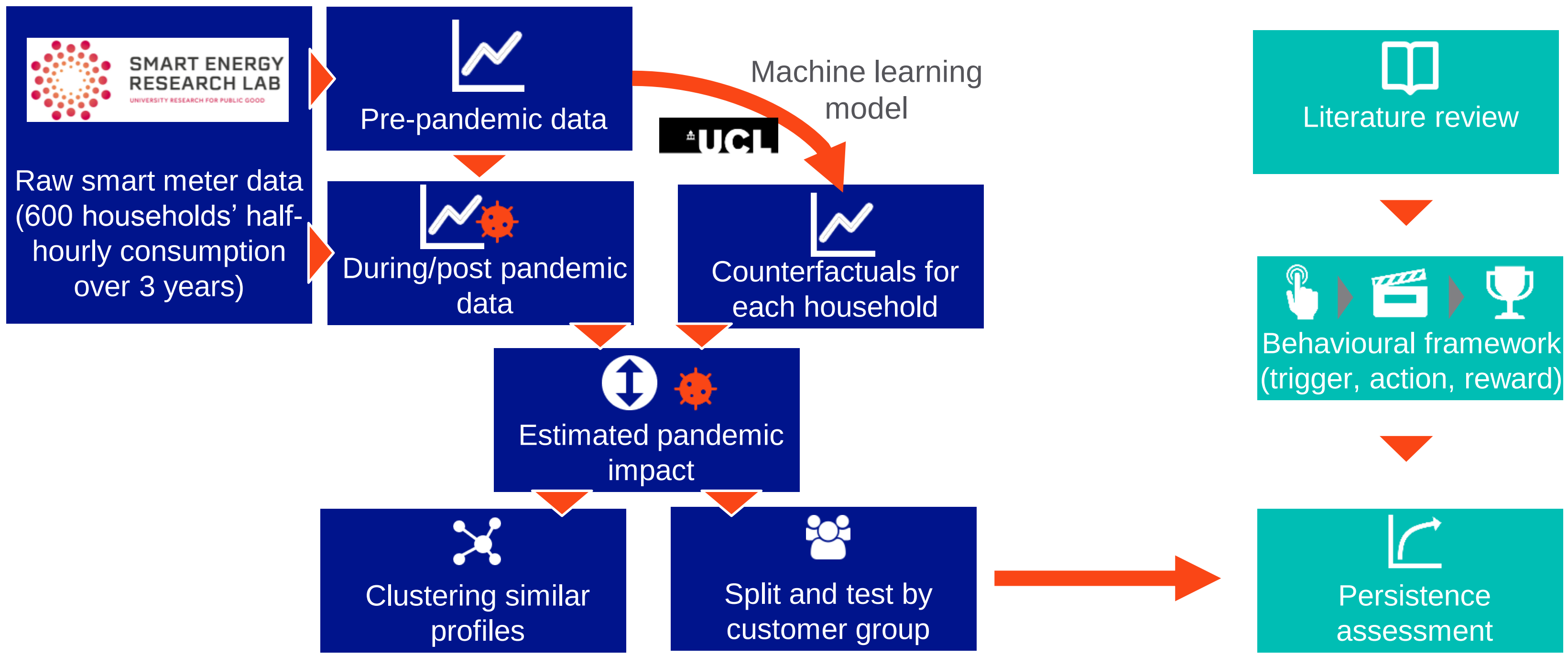
…the cost of living crisis on electricity and gas consumption…

…on customers in vulnerable situations, and DNOs' networks

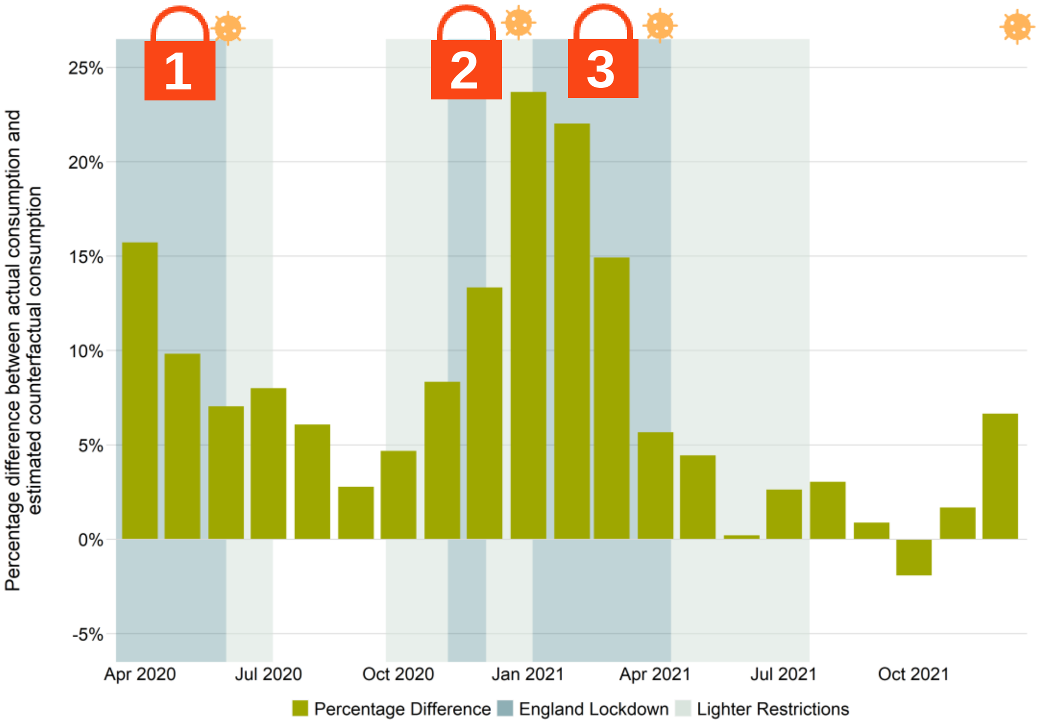
Machine learning was used alongside behavioural analysis to unpick different responses to the pandemic

Quantitative analysis

Qualitative analysis

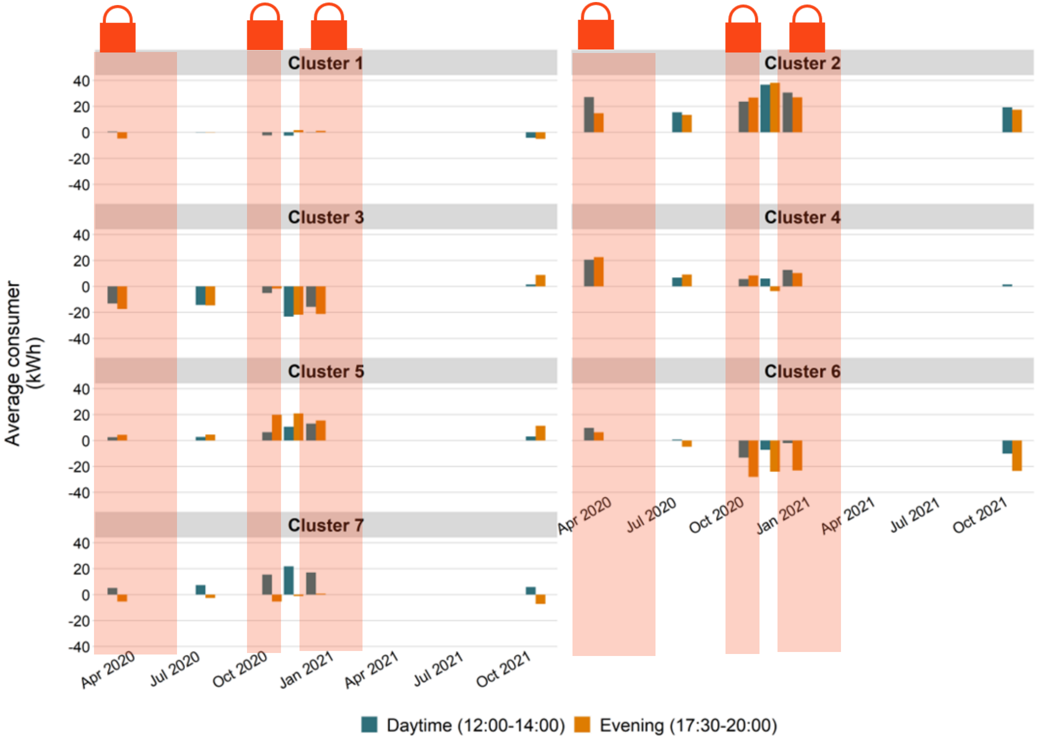


Average daytime consumption increased during lockdowns, but on average this effect did not persist



- Increases in daytime (12:00 – 14:00) demand of nearly 25% (Jan-21)
- Less impact (< 10%) on the evening peak
- Some impact of Omicron (Dec-21) despite no official lockdown

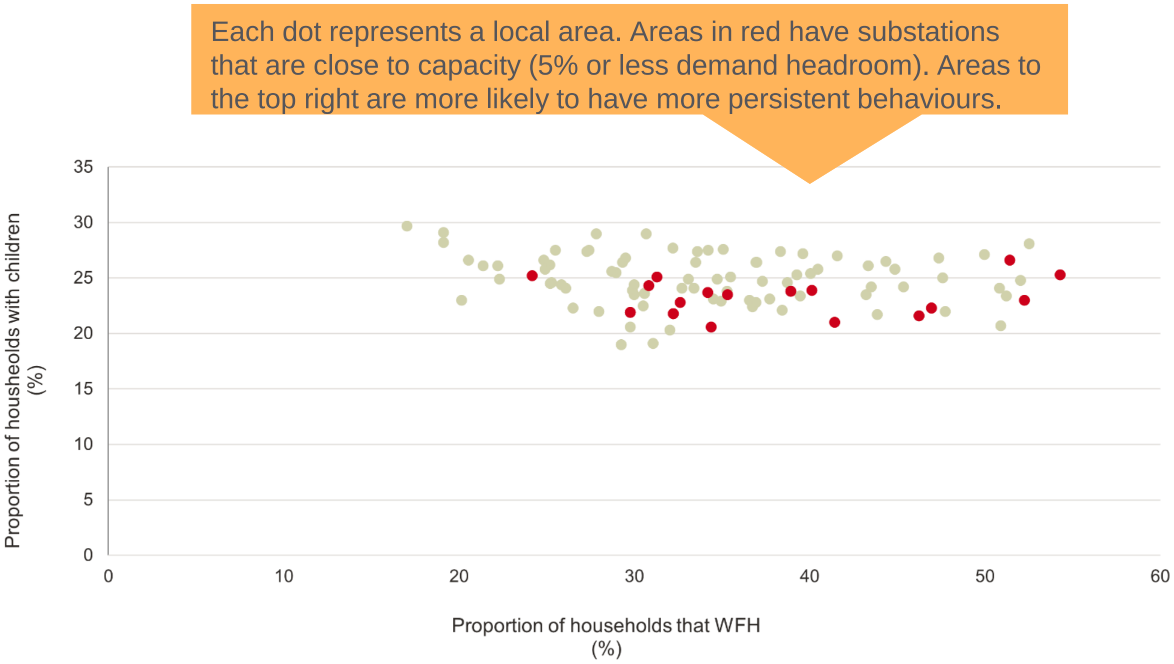
This aggregate impact hides very different behaviours at the household level



- Nearly a third of households barely changed consumption throughout (cluster 1)
- But cluster 2 (8% of households) had a strong impact which persisted (at least to Nov-21*)
- Greater persistence for those with children and those WFH
- Less consumption (and bill) increases for those on lower incomes – so unlikely to substantially increase fuel poverty

*The final month of non-lockdown period before Omicron wave

Implications of changed consumption on the network likely to be small and localised

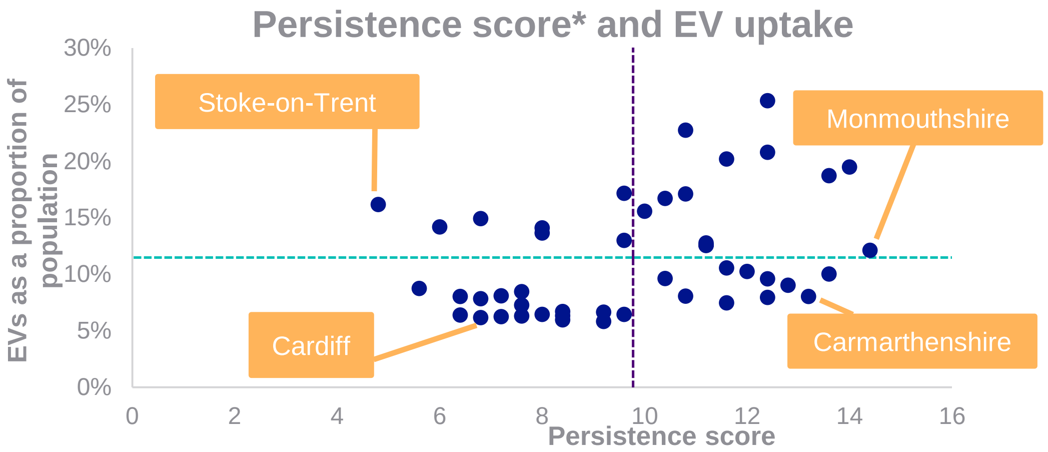


- Even at the height of the pandemic, increase in *peak* demand was only 5% so limited impact on network
- But this may concentrated in certain areas, where network forecasts may need updating (areas highlighted in red)
- Not all these areas will have customers with persistent behaviours

The pandemic impacted travel patterns which may affect future EV charging demand in different locations

Impact of covid on travel patterns → **Analysis of distribution and persistence of behaviour** → **Mapping to EV ownership** → **Implications for charging in ED2**

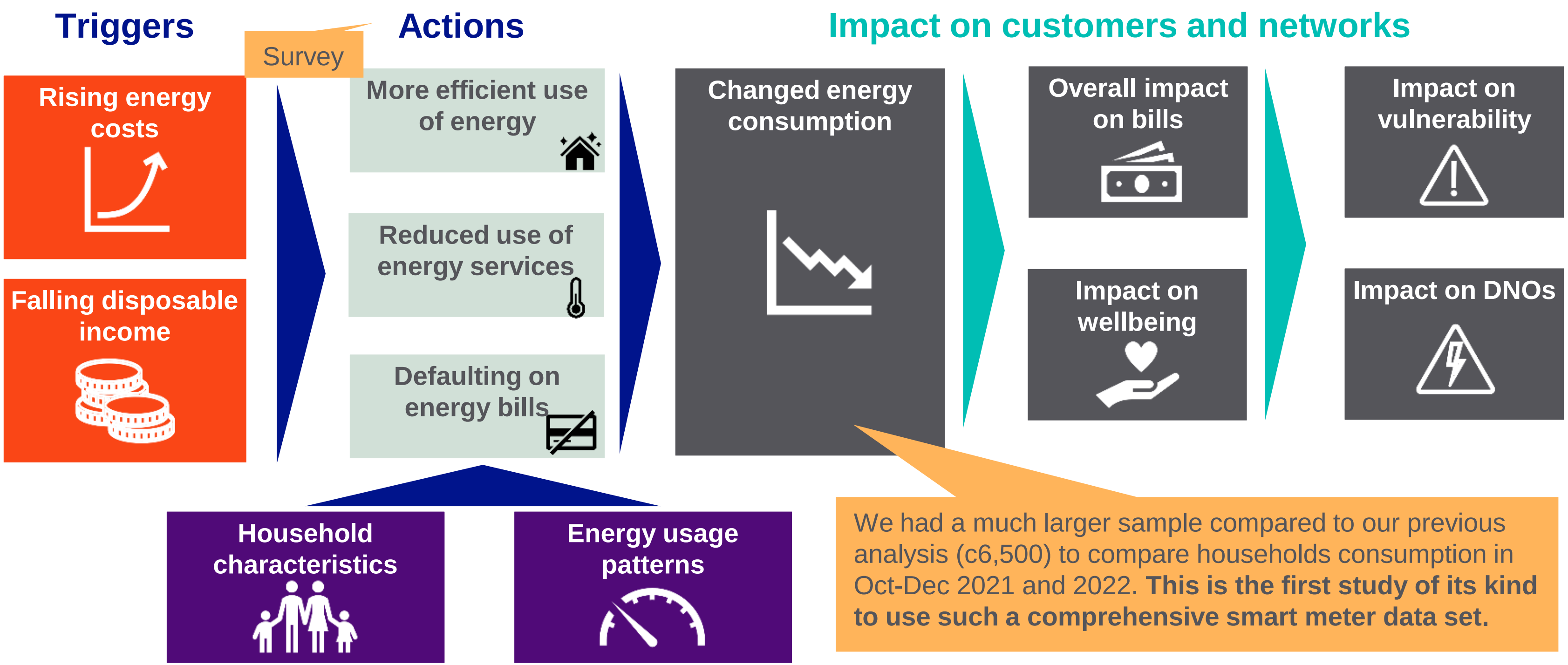
Aim to understand what persistent WFH means for future EV charging demand



- Some areas (like Monmouthshire and Carmarthenshire) are likely to have persistent WFH behaviour
- This makes them more likely to have different EV usage compared to pre-pandemic expectations
- Other areas will have more similar behaviour to pre-pandemic (such as Stoke-on-Trent and Cardiff)

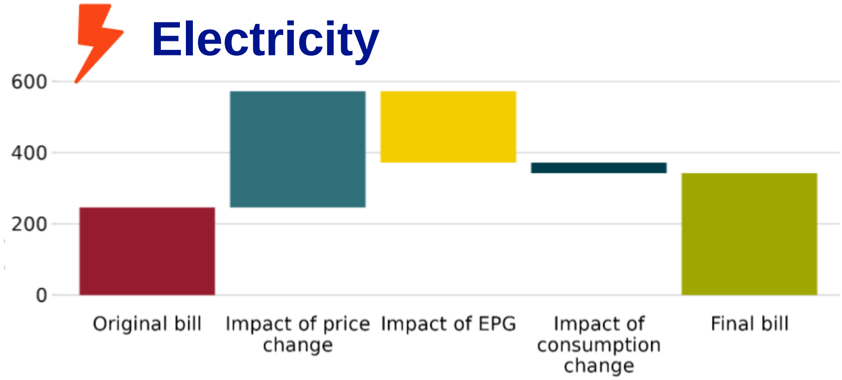
*We created a persistence score to proxy for the level of persistence in a local area

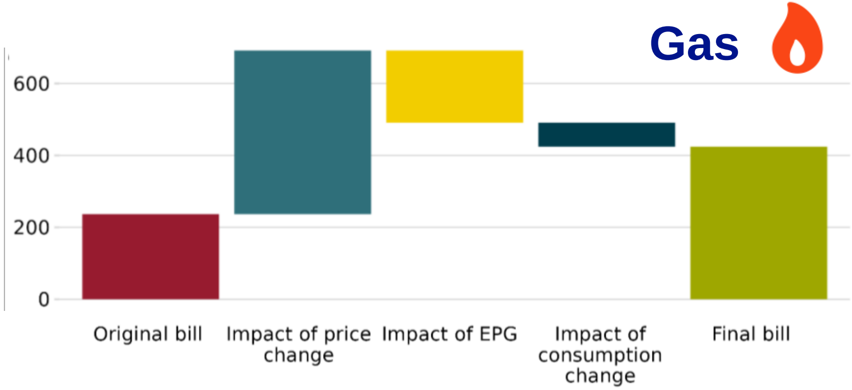
We used a large smart meter data sample (elec & gas) alongside a survey to understand the impact of the COLC



We had a much larger sample compared to our previous analysis (c6,500) to compare households consumption in Oct-Dec 2021 and 2022. **This is the first study of its kind to use such a comprehensive smart meter data set.**

Electricity and gas consumption fell substantially in Oct-Dec 2022, but not enough to offset price increases





- Typical quarterly electricity bills rose by **£75**, with consumption reductions avoiding a further **£29** increase

- Typical quarterly gas bills rose by **£150**, with consumption reductions avoiding a further **£69** increase

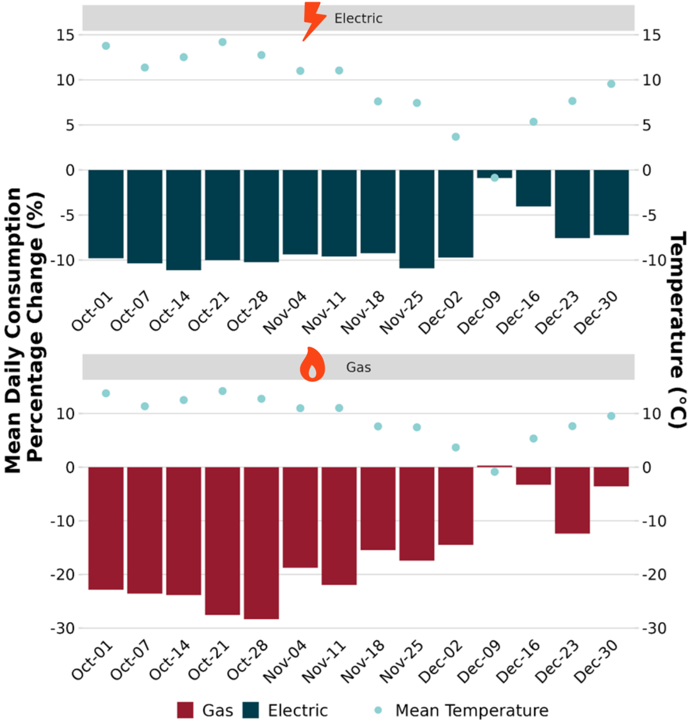
Despite decreased consumption, we estimate the proportion of our sample in fuel poverty increased from 12.5% to 15.7%

The reduction in demand lessened when the weather became colder in December

- By 9th December, when the weather was coldest, gas and electricity consumption reverted back to almost exactly predicted consumption

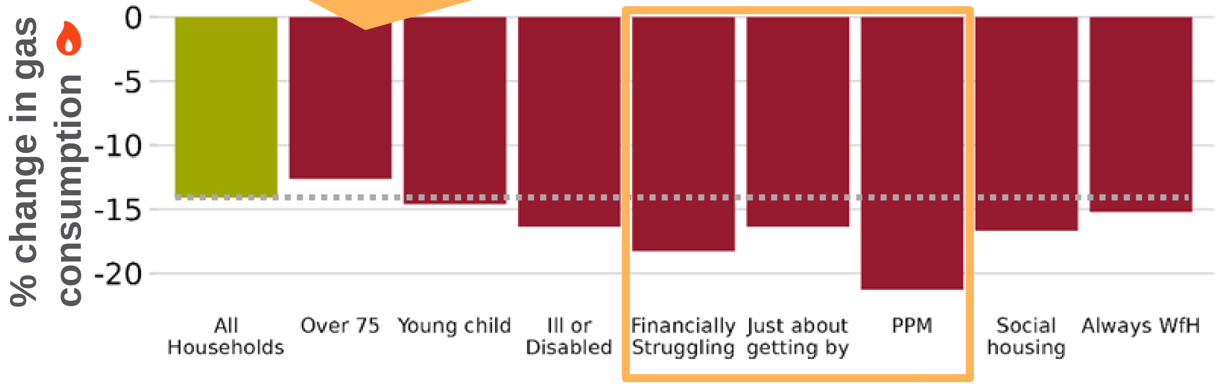
- When temperatures began to warm, behaviour did not entirely revert back (although Christmas and New Year makes this period harder to assess)

- Without later data we cannot tell if savings resumed once the weather warmed up, or if this 'shock' had a longer-term impact



Customers in different vulnerable situations responded in very different ways

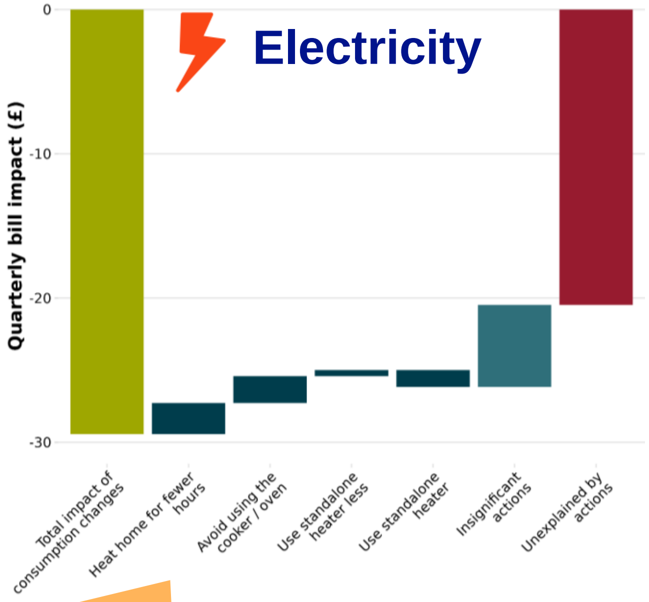
Households with elderly members changed consumption least – they may have prioritised heating the home. This could be because they received more energy support payments.

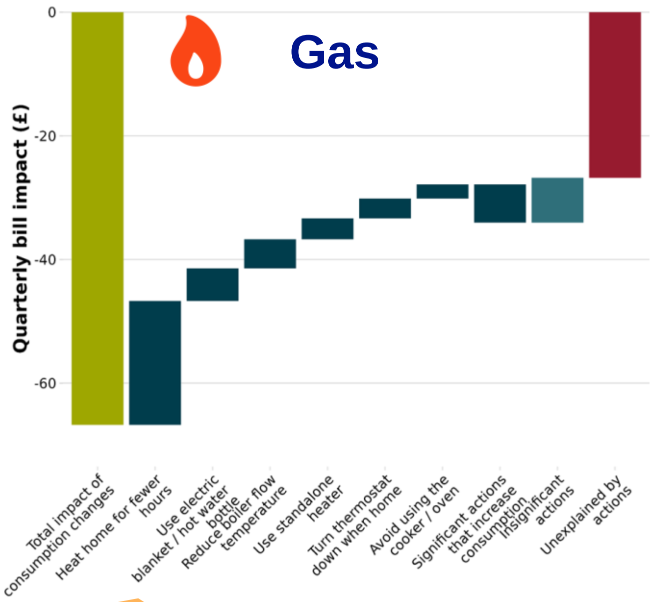


Households reporting financial issues, and those on PPM meters, decreased consumption the most – these vulnerable groups may be under-heating their homes.

Figures shown for gas consumption – electricity results similar, but smaller changes

Taking action to reduce energy consumption had an impact, but some actions are more effective than others





Actions to save electricity were generally less effective; bill savings can be attributed to other household changes

There were more effective actions to reduce gas consumption; heating homes for fewer hours was the most effective action (although many others were significant)

There are implications for NGED in terms of network planning and customers in vulnerable situations

Network planning

Ensure domestic consumption is kept under review as price pressures continue

Understand where customers are using more electricity than expected

Understand how heat pump customer behaviour compares to gas boiler behaviour

Gather evidence on flexible use of heat pumps

Customers in vulnerable situations

Consider what effective energy-saving advice will be for customers with heat pumps

Focus outreach on groups likely to be in fuel-poor households

Provide energy-saving advice to customers through trusted partners

Electricity Distribution

Smart Meter Data and Vulnerability Research

Zoe Hodgins
Frazer-Nash Consultancy

nationalgrid

Aims

1. **Identify behaviours customers in vulnerable situations (CIVS) may exhibit**
2. **Determine if it is possible to detect CIVS from their smart meter data**
    a) Cohort Comparison
    b) Appliance disaggregation & Disaggregation
    c) Overall Changes in Usage
3. **Disseminate learnings to stakeholders**

Vulnerability Outreach: Approach

Our team of behavioural scientists researched how CIVS may interact with their electricity differently.

We completed the work in three phases:

1. Literature Review
2. Consultation Period
3. Behavioural Analytics

Split vulnerabilities into types:

- Financial: fuel poverty, complex vulnerability
- Health & capacity-related factors: physical health, mental health, mental capacity, age
- Geographic & location: rurality, digital services, household tenure, high risk of environmental damage

Vulnerability Outreach: Key Findings

1. Complex relationship and correlations between vulnerability factors
   - Vulnerability should be considered as a continuum rather than as a category
   - Consider a degree of vulnerability and allow for worst-first service provision

2. Confirmed hypothesis of the vulnerabilities that are likely to be identifiable in electricity usage
   - Medical appliances, night-time usage, changing circumstances, fuel poverty

3. Allow operators to access smart meter data
   - Allows DNOs to understand, support and anticipate consumer circumstances and energy demands
   - Use of a probabilistic model of smart meter data for the purposes of predicting vulnerability was supported

4. Should combine data sources to improve understanding and identify vulnerabilities
   - Energy Usage (smart meter data), account history, known household characteristics

Identifying Vulnerability from Smart Meter Data: Approach

Cohort Comparison	To identify vulnerabilities related to the overall level of usage a specific household has	• Too high and maybe poorly insulated • Too low and maybe struggling to pay bills
Appliance Disaggregation and Prediction	To identify vulnerabilities related to appliance usage	• Medical devices • Erratic use of appliances indication cognitive difficulties
Overall Changes in Usage	To identify vulnerabilities related to a significant change in its occupants' behaviour	• Job loss • New carer • Consciously reducing usage

Datasets Used

- Each model was trained and tested in isolation using different data sources
- Spent most of the project using open-source datasets:
  - UKPN LCL Project: Household level smart meter data but no household information
  - UKEDC & REFIT: Appliance power monitoring at 10sec and 30sec intervals across 20+ households
  - LSOA features: Average annual household usage and household types
- In the latter stages of the project, Hildebrand provided data for 5,000 households with known features

Office for National Statistics

hildebrand

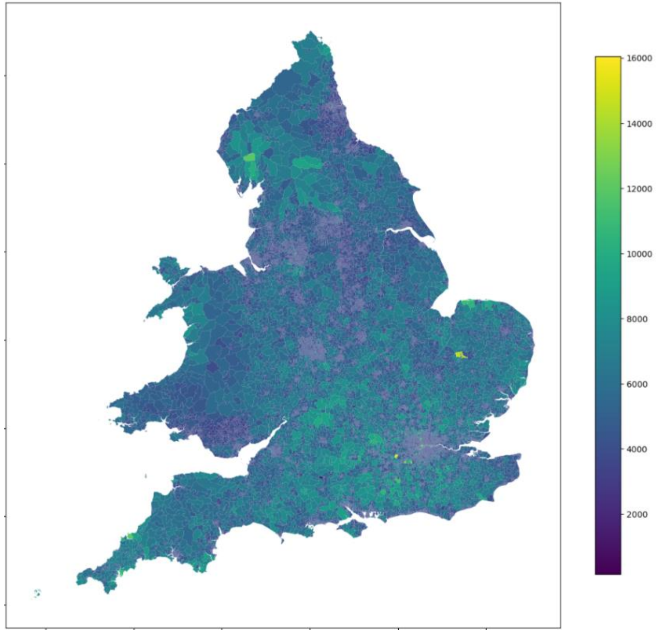
Cohort Comparison: Approach

Aim: Predict if someone was vulnerable based on their known energy usage and household characteristics (location, EPC etc)

Challenge: We did not have household level usage with known household characteristics

Solution: Developed a model for predicting the average annual energy usage for all households within an LSOA as a proxy.

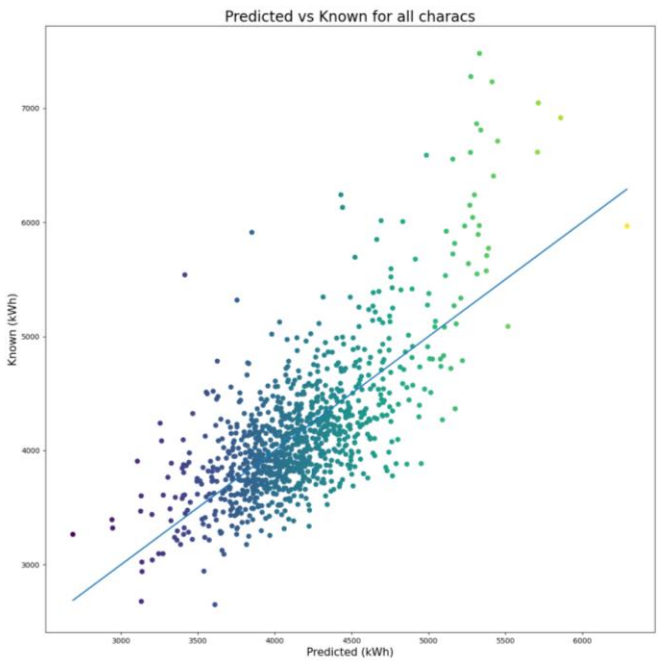
- Determine characteristics for the ~800 households within the LSOA: EPC, age, number occupants, accommodation type, heating type
- Develop machine learning model to predict the annual average energy usage
- Determine if a household is within the prediction, and if not, they are comparatively low or high to expectations



Heatmap of England and Wales showing the average energy usage per household per Lower Super Output Area (LSOA).

Cohort Comparison: Key Findings

- Can predict average annual energy usage to within 15% from the household characteristics
- Most of this uncertainty is due to the datasets
- Investigation showed some unaccounted-for variation:
    - Household features not included, such as health
    - Variation in human behaviour
    - Geographic or other social factors
- Implies you cannot predict average annual energy usage on household characteristics alone
- To draw more accurate conclusions, would require household level datasets



Scatter of known annual energy usage per LSOA against predicted.

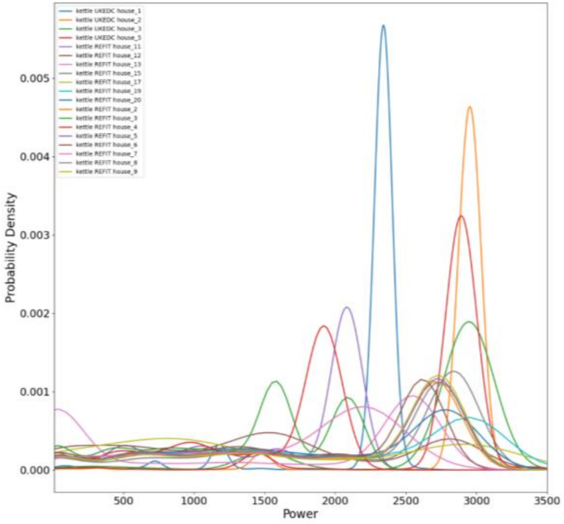
Appliance Disaggregation and Prediction: Approach

Aim: Determine how a household is using its appliances, to identify medical devices and erratic usage.

Challenge: Large amount of academic research into load disaggregation using various machine learning techniques. Conclusions to date show this remains very difficult with 30minute resolution.

Solution: Use a probabilistic method to directly account for uncertainties in energy used by appliances.

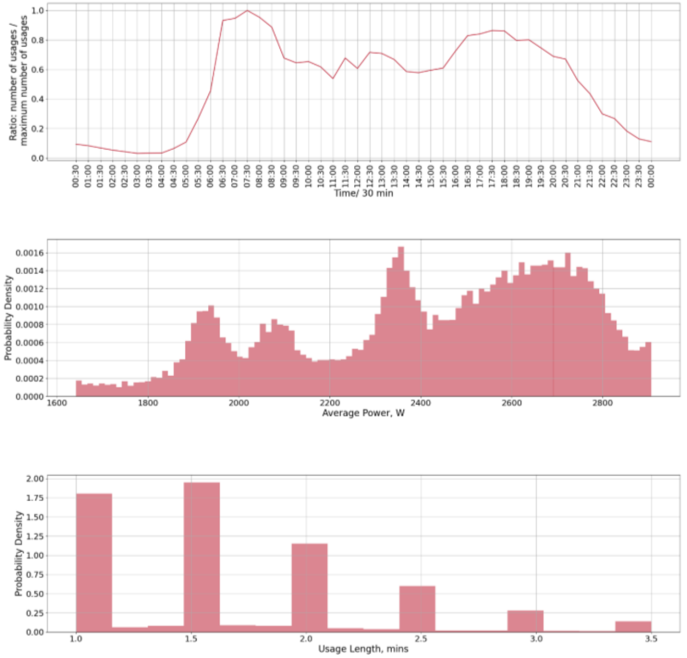
- Determine the energy drawn by household appliances, accounting for:
  - Differences in make, model and age
  - Changes in how much power the appliance draws, and for how long, when used in different ways
- Learn how the household uses its appliances



Gaussian kernel-density estimates of the power drawn by kettles across 19 households.

Appliance Disaggregation and Prediction: Key Findings

- Calculated statistical representations of the amount of energy different household appliances could draw.
- Developed model to determine probability each appliance is being used, for a given energy usage.
- Implemented model ‘learning’ to reduce the uncertainty through time.
- Showed that we could identify appliances in simple use cases.
- Even with probabilistic method, the uncertainty in the power drawn by appliance was the biggest challenge.
- To improve the model, you could:
  - Obtain higher resolution data, ~1minute would be required.
  - Increase complexity of learning algorithm to reduce appliance uncertainty.



Usage statistics extracted for the kettle.

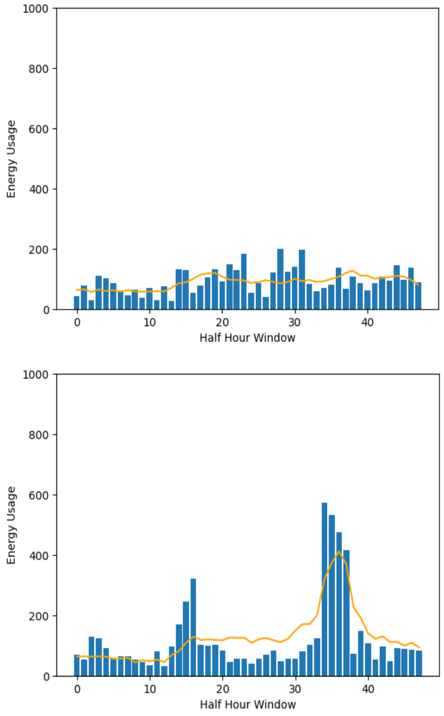
Overall changes in Usage: Approach

Aim: Determine if a household has changed its usual usage pattern

Challenge: Human behaviour is very variable, and any model developed cannot be sensitive to small fluctuations in behaviour.

Solution: Develop an ML outlier detection model that is formulated from historic behaviour of the household.

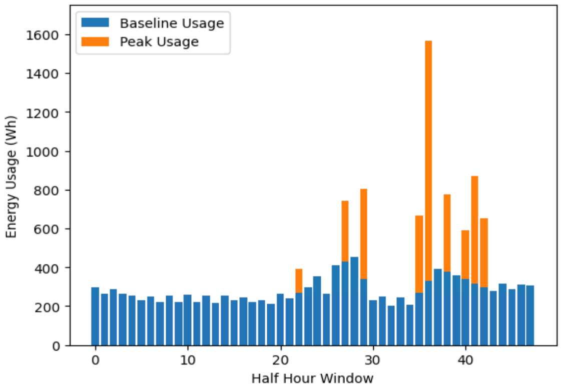
- Remove extreme peaks in usage but retain total energy used each day
- Cluster each day of energy usage (30min increments)
- Develop classifier to look at new day and determine which cluster it goes into
- A change is detected if:
    - A new day does not fit in to the existing clusters for that household
    - The proportion of days in each cluster changed significantly



Energy usage over randomly selected days within two clusters for a household

Overall changes in Usage: Key Findings

- Clustering and outlier detection model was produced to detect changes in usage for a household
- The model was shown to work well on most changes implemented within the households
- Found most households have four types of day and always includes:
  - Holiday days: low usage throughout
  - At home days: high usage throughout
- Removing erratic spikes in usage allows sporadic behaviours to be removed and underlying behavioural patterns are retained
- Model could be improved by:
  - Adding in more contextual information, such as holidays and weather
  - Test on households with known changes in behaviour



Distribution of energy usage over a single day for a household, with baseline and peak usage separated.

Identifying Vulnerability from Smart Meter data: Overall Conclusions

- Three models were developed to detect different types of vulnerabilities from household smart meter data.
- Found that household usage is dependent on household features (such as EPC), but also occupant features (such as employment and age).
- Determined how different household appliances are used.
- Found that we could identify some appliance usage from 30-minutely data, but to improve accuracy and include medical devices, usage to 1 minute would be required.
- A clustering and outlier detection model can detect sustained changes in a household's behaviour.

Dissemination

1. Demonstrator Dashboard

To demonstrate how a model like VENICE could be used to identify vulnerable households.

Allows user to explore patterns in real household smart meter data and learn how the model works.

https://venice.fnc.digital

Works on any webpage, although significantly easier to view on a computer screen.

2. Reporting

Reports can be found on the National Grid website:

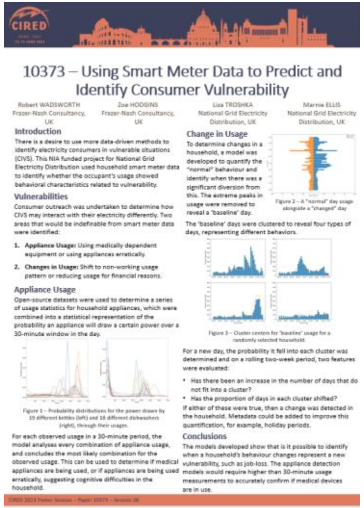
- Detailed findings and conclusion from the vulnerability outreach work
- Detailed model development methodologies for:
  - Cohort Comparison
  - Appliance Disaggregation & Prediction
  - Overall Change Detection

https://tinyurl.com/5y5hn7y9

3. CIRED

Results were presented at the International Conference for Electricity Distribution (CIRED) in June 2023.

The research paper and poster can be found on the website.


CIRED

10373 – Using Smart Meter Data to Predict and Identify Consumer Vulnerability

Robert WADSWORTH, Frazer-Nash Consultancy, UK
Zoe HODGINS, Frazer-Nash Consultancy, UK
Liza TROSHKA, National Grid Electricity Distribution, UK
Marnie ELLIS, National Grid Electricity Distribution, UK

Introduction

There is a desire to use more data-driven methods to identify electricity consumers in vulnerable situations (CIVS). This NIA funded project for National Grid Electricity Distribution used household smart meter data to identify whether the occupant's usage showed behavioral characteristics related to vulnerability.

Vulnerabilities

Consumer outreach was undertaken to determine how CIVS may interact with their electricity differently. Two areas that would be indefinable from smart meter data were identified:

1. **Appliance Usage:** Using medically dependent equipment or using appliances erratically.
2. **Changes in Usage:** Shift to non-working usage pattern or reducing usage for financial reasons.

Appliance Usage

Open-source datasets were used to determine a series of usage statistics for household appliances, which were combined into a statistical representation of the probability an appliance will draw a certain power over a 30-minute window in the day.

Figure 1 – Probability distributions for the power drawn by 19 different kettles (left) and 18 different dishwashers (right), through their usages.

For each observed usage in a 30-minute period, the model analyses every combination of appliance usage, and concludes the most likely combination for the observed usage. This can be used to determine if medical appliances are being used, or if appliances are being used erratically, suggesting cognitive difficulties in the household.

Change in Usage

To determine changes in a household, a model was developed to quantify the "normal" behaviour and identify when there was a significant diversion from this. The extreme peaks in usage were removed to reveal a 'baseline' day.

Figure 2 – A "normal" day usage alongside a "changed" day

The 'baseline' days were clustered to reveal four types of days, representing different behaviors.

Figure 3 – Cluster centers for 'baseline' usage for a randomly selected household.

For a new day, the probability it fell into each cluster was determined and on a rolling two-week period, two features were evaluated:

- Has there been an increase in the number of days that do not fit into a cluster?
- Has the proportion of days in each cluster shifted?

If either of these were true, then a change was detected in the household. Metadata could be added to improve this quantification, for example, holiday periods.

Conclusions

The models developed show that is it possible to identify when a household's behaviour changes represent a new vulnerability, such as job-loss. The appliance detection models would require higher than 30-minute usage measurements to accurately confirm if medical devices are in use.

Electricity Distribution

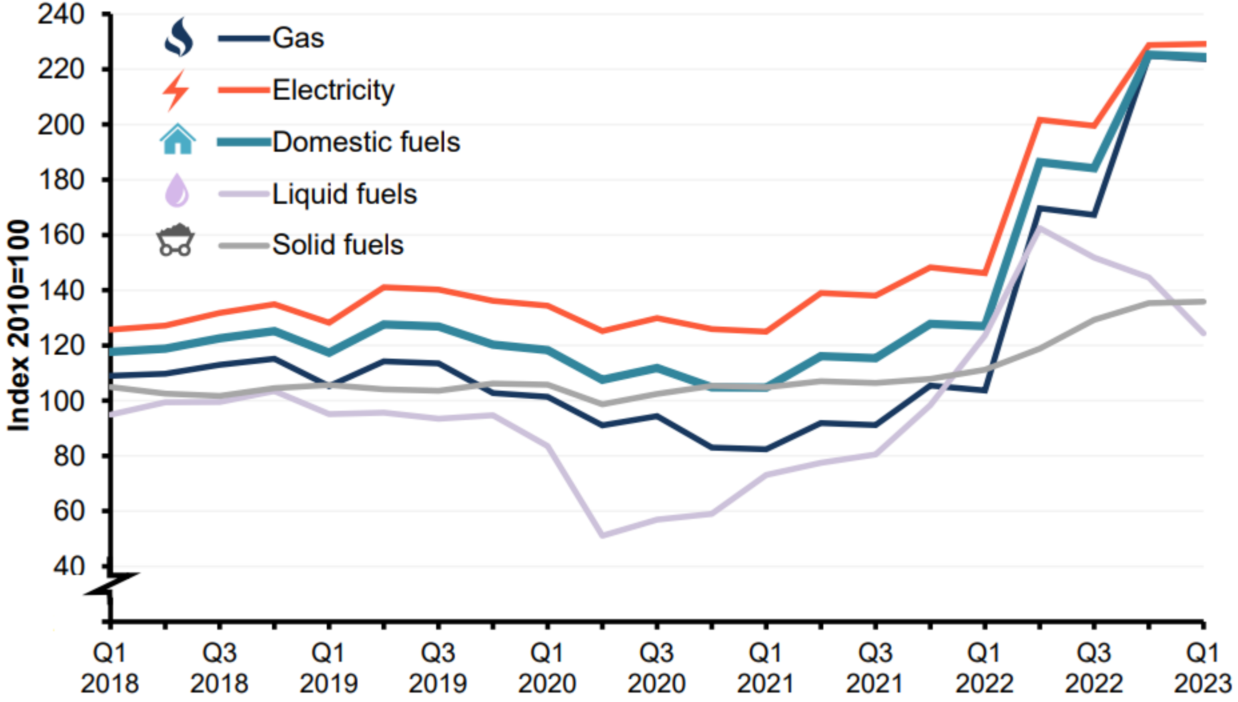
Community Energy Engagement and Net Zero

Chris Coonick
Technical Director, Wadebridge Renewable Energy Network (WREN)

nationalgrid

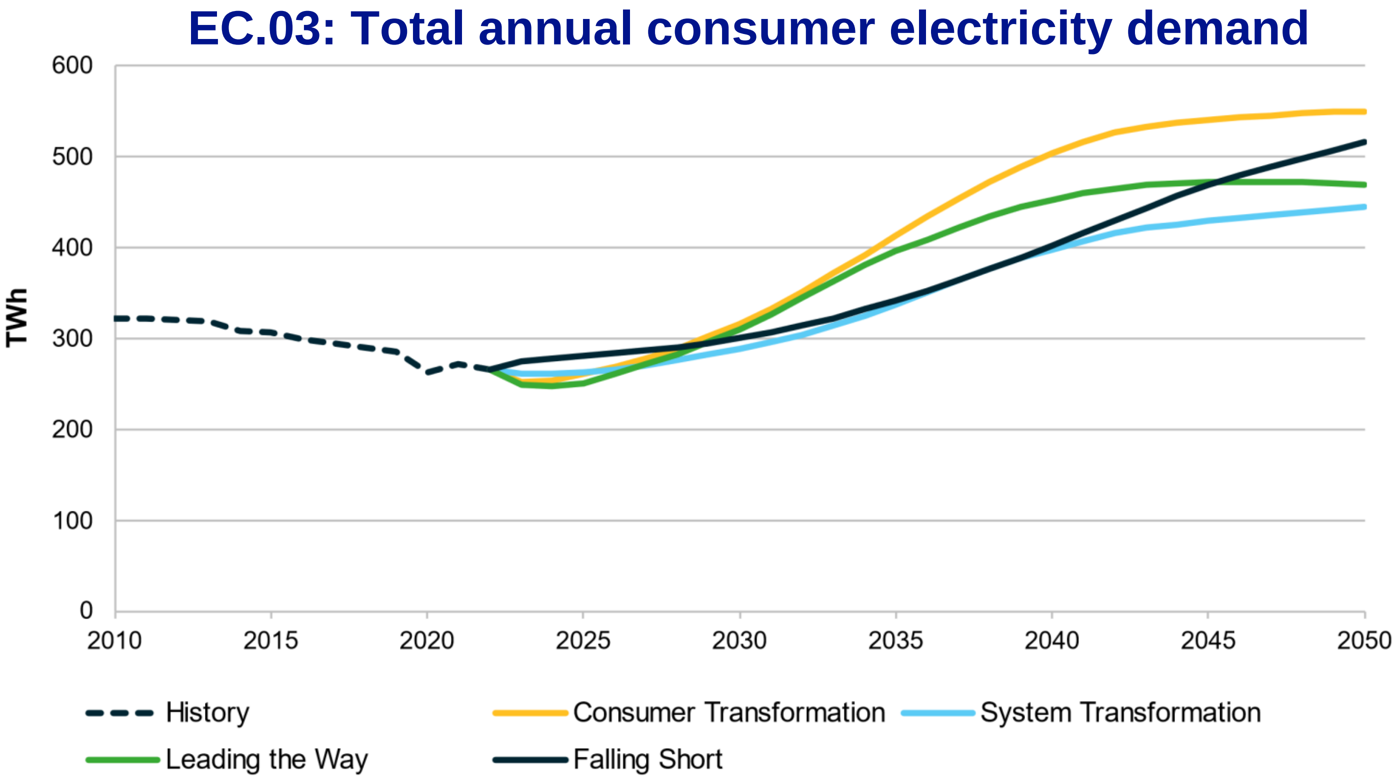
What’s the problem? Supply

Chart 2.1 UK real term domestic energy price indices



Source: Office for National Statistics, Quarterly Energy Prices (June 2023)

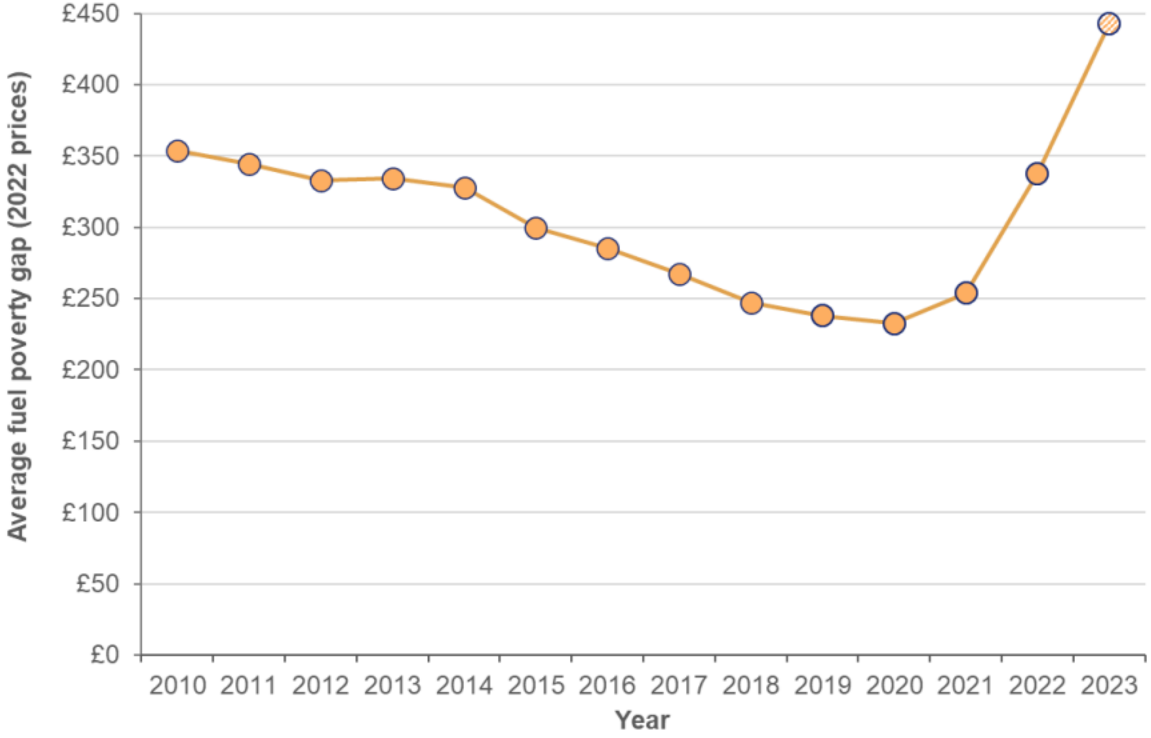
What’s the problem? Demand



Source: National Grid, Future Energy Scenarios (2023)

What’s the problem? Impact

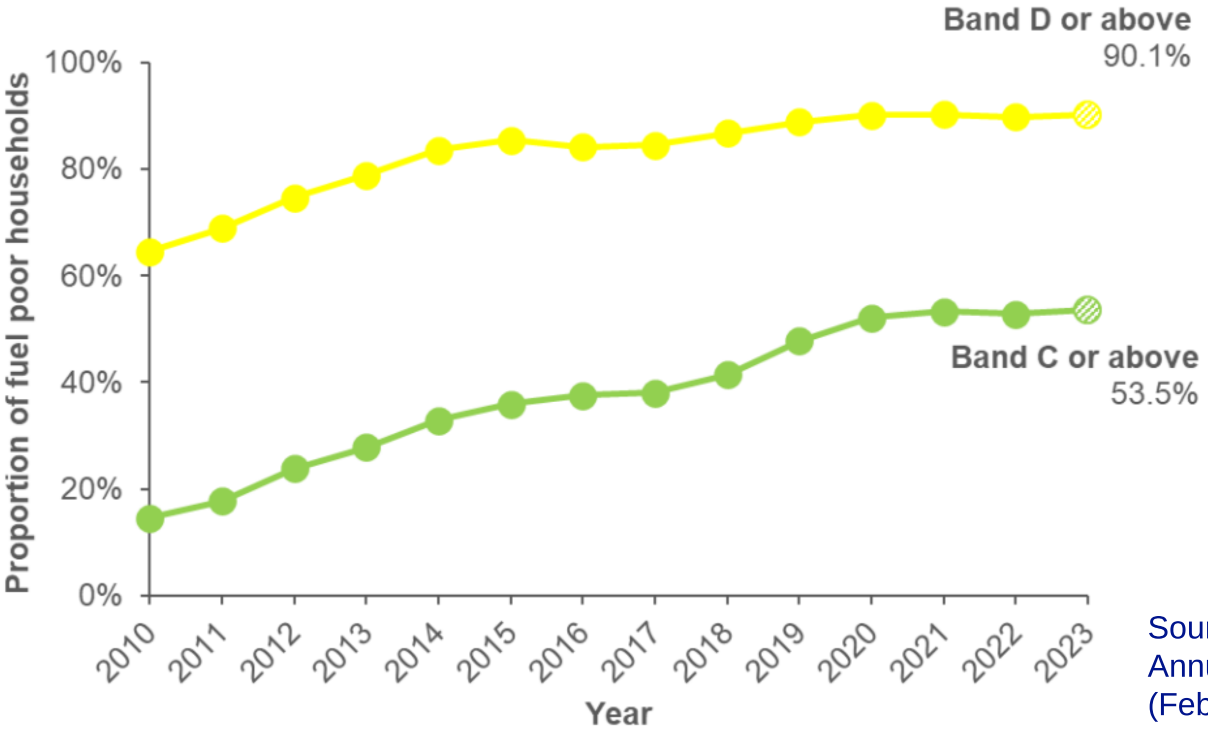
Fig 4.2: Average fuel poverty gap in UK



Source: Office for National Statistics, Annual Fuel Poverty Statistics England (Feb 2023)

What’s the problem? Impact

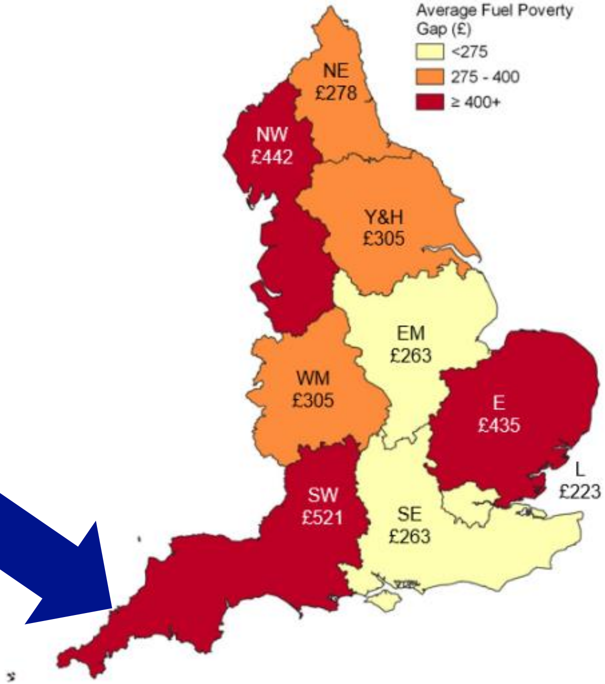
Fig 4.4: Energy efficiency of homes & fuel poverty



Source: Office for National Statistics, Annual Fuel Poverty Statistics England (Feb 2023)

What’s the problem? Impact

Fig 3.10: Average fuel poverty gap across England



Source: Office for National Statistics, Annual Fuel Poverty Statistics England (Feb 2023)

Net Zero Community (NZCom)

This project was a collaboration between:

- Wadebridge Renewable Energy Network (WREN) – community engagement and project management
- University of Exeter – future energy scenarios and carbon accounting
- Planet A Solutions – impact and mitigation
- Community Energy Plus – community business models and vulnerable customer insights

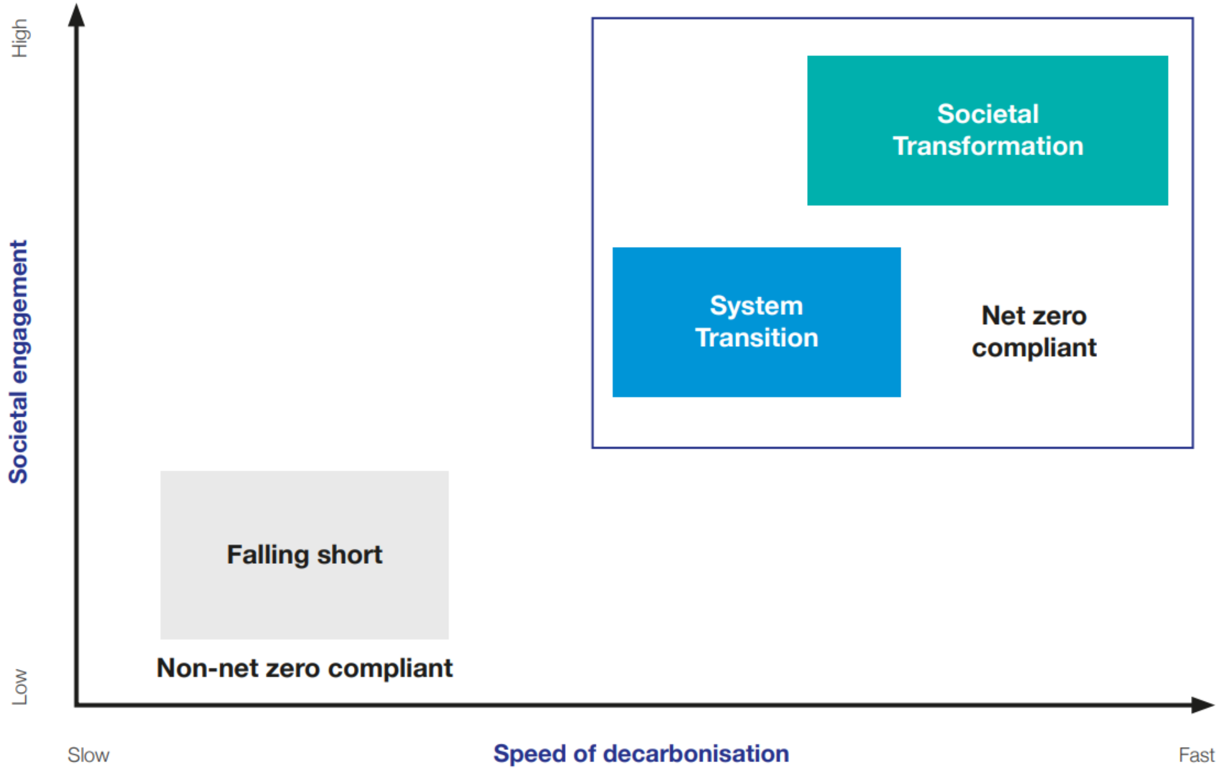
Supported by the Centre for Energy Equality

Leaving no one behind

What we achieved

- Developed future likely net zero scenarios to 2050 for the Wadebridge & Padstow Community Network Area.
- Developed a carbon accounting methodology to qualitatively compare impacts and interventions.
- Identified technologies, systems, and approaches to reach net zero in Wadebridge by 2050 that positively support vulnerable customers.
- Developed community-led business models that have the potential to deliver socioeconomic benefits and are supported by the local community.
- Published & shared tools, methodologies & learnings for other communities to define their own 2050 net zero models & support planning.
- Engaged with 1000+ members of our community & won an award!

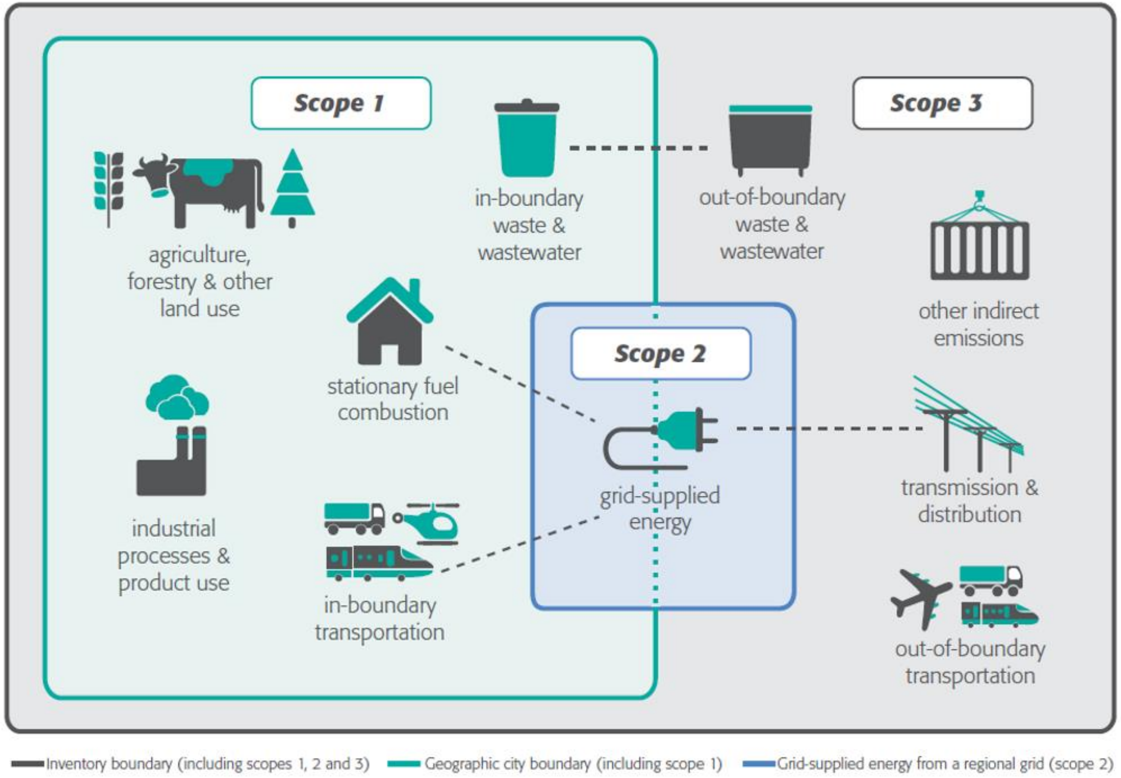
Future energy scenarios for net zero



What pathway should you take?

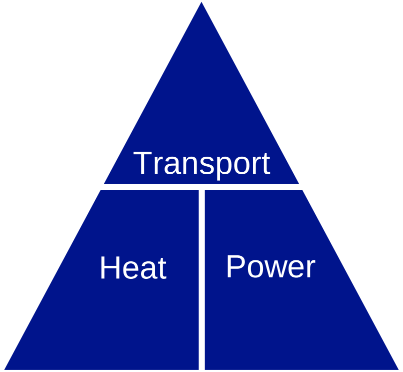
- Multiple, plausible energy system futures exist, but achieving net zero by 2050 is not inevitable
- Change is systemic, pathways will be influenced by interconnected technological, economic, behavioural, and political factors.
- Improvements to thermal efficiency of existing buildings is universally accepted as a no-regrets option.
- Some progress towards decarbonisation may be made with minimal societal engagement.
- It is possible to address decarbonisation to an extent, without addressing vulnerabilities.
- A plausible scenario exists in which decarbonisation is aligned with environmental, societal, and economic co-benefits.

If you can’t measure it, you can’t manage it

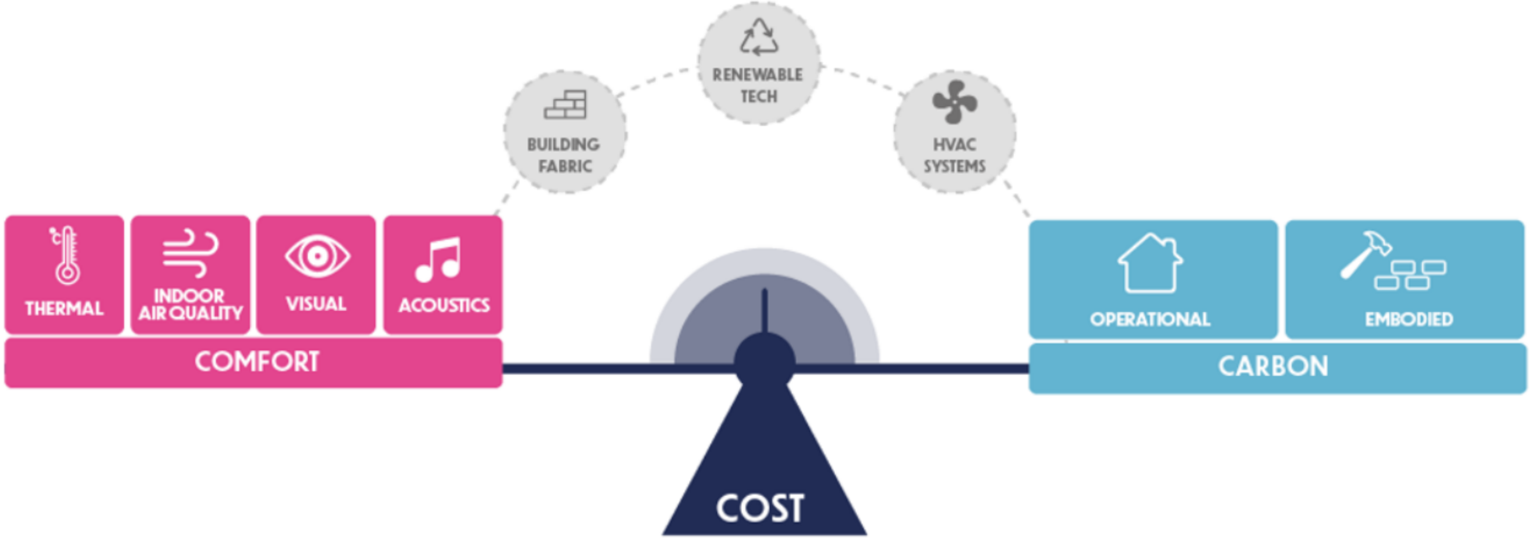


Technical solutions for a net zero future

1	**Understand the challenge**	**Gather a strong team**	Engineers, scientists, project managers, architects.
2	**Initial ideas register**	**Rate ideas**	Against GHG emission reductions, technical and regulatory feasibility, simplicity and community benefit.
3	**Understand the building mix**	**Collect information**	Consider building fabrics, how energy is used, what is the mix of gas, oil, wood, electricity for heating?
4	**Develop a solutions package**	**Review technical and system options**	What works for your area? Consider constraints and methodology to deliver.
5	**Carbon modelling**	**Use the NZCom community tool**	Input data from the community to understand the starting point and the impact of different actions.



It’s a balancing act



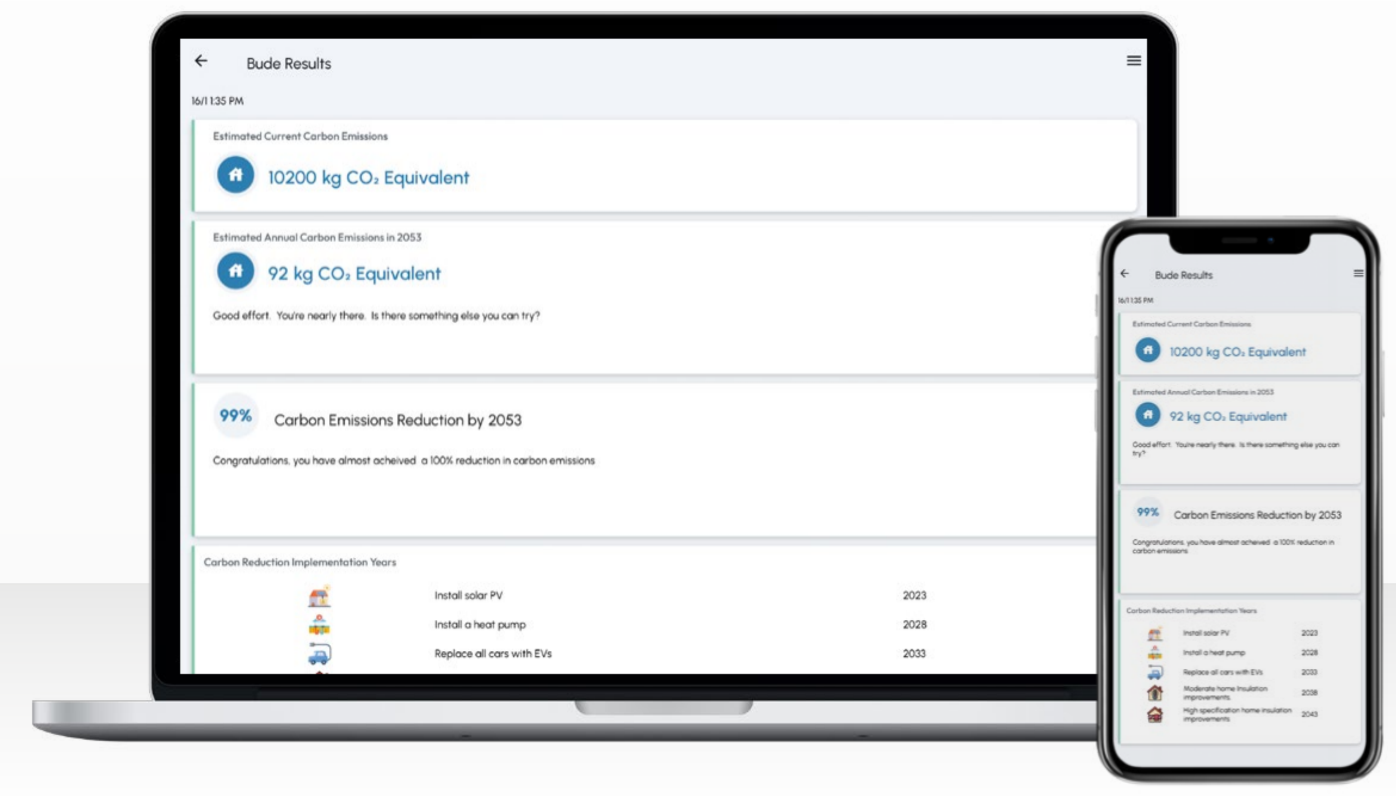
What can a community group do?

Education

Facilitation

Action

Future Energy Tool for Communities



https://nzcom.cee-uk.com/

Published outputs from NZCom

Future energy scenarios and carbon accounting

- Review of future energy scenarios and associated methodologies
- High level net zero scenarios developed for the Wadebridge and Padstow Community Network Area
- Community scale NZC 2050 carbon accounting method

Impact and mitigation

- Review of technical and system options
- Characterisation of confining factors to meet net zero
- Net Zero 2050 Report: Wadebridge and Padstow Community Network

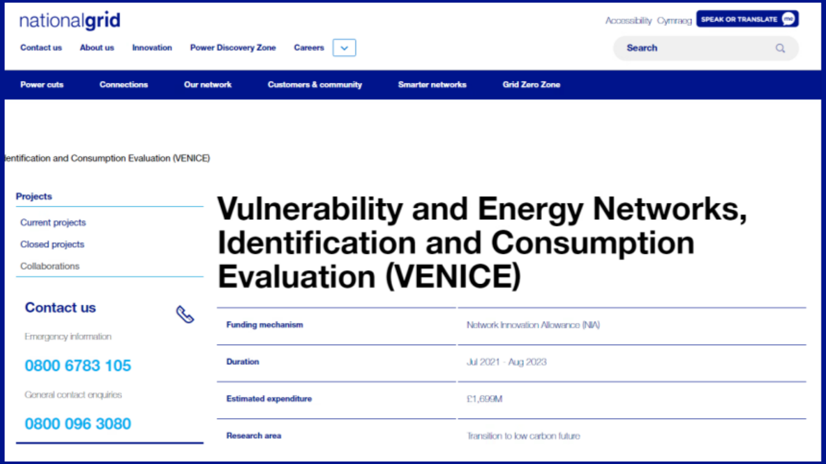
Community business models and vulnerable customer insights

- Establishing socioeconomic outcomes of community business models
- Community business models options paper & proposal
- Vulnerability of domestic consumers
- Working definition of vulnerability of non-domestic consumers

https://tinyurl.com/5y5hn7y9

VENICE whole summary

All information available on NG Innovation Webpage:



https://tinyurl.com/5y5hn7y9

Community Energy Support

Faithful Chanda
Title: Development Engineer (Community Energy)

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Email: fchanda@nationalgrid.co.uk

- To help new community energy schemes connect to our network
- To build community energy groups' capabilities to participate in, and benefit from, flexibility markets
- Through: Community Energy Workshops, Connections Surgeries, Workshops and Customer Steering Group

Q&A

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