International Energy Agency
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Data-driven modelling of behaviour in energy planning models

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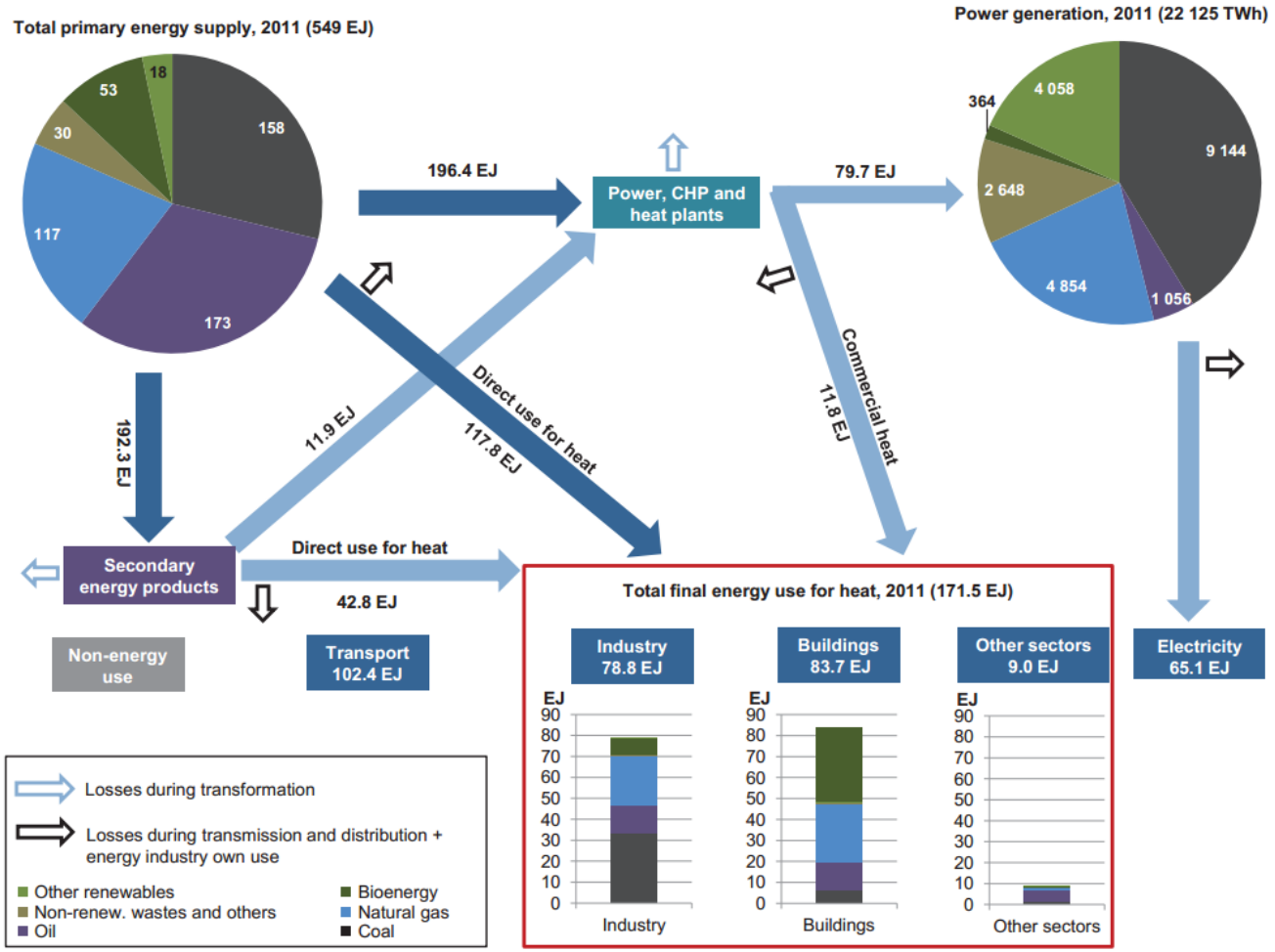
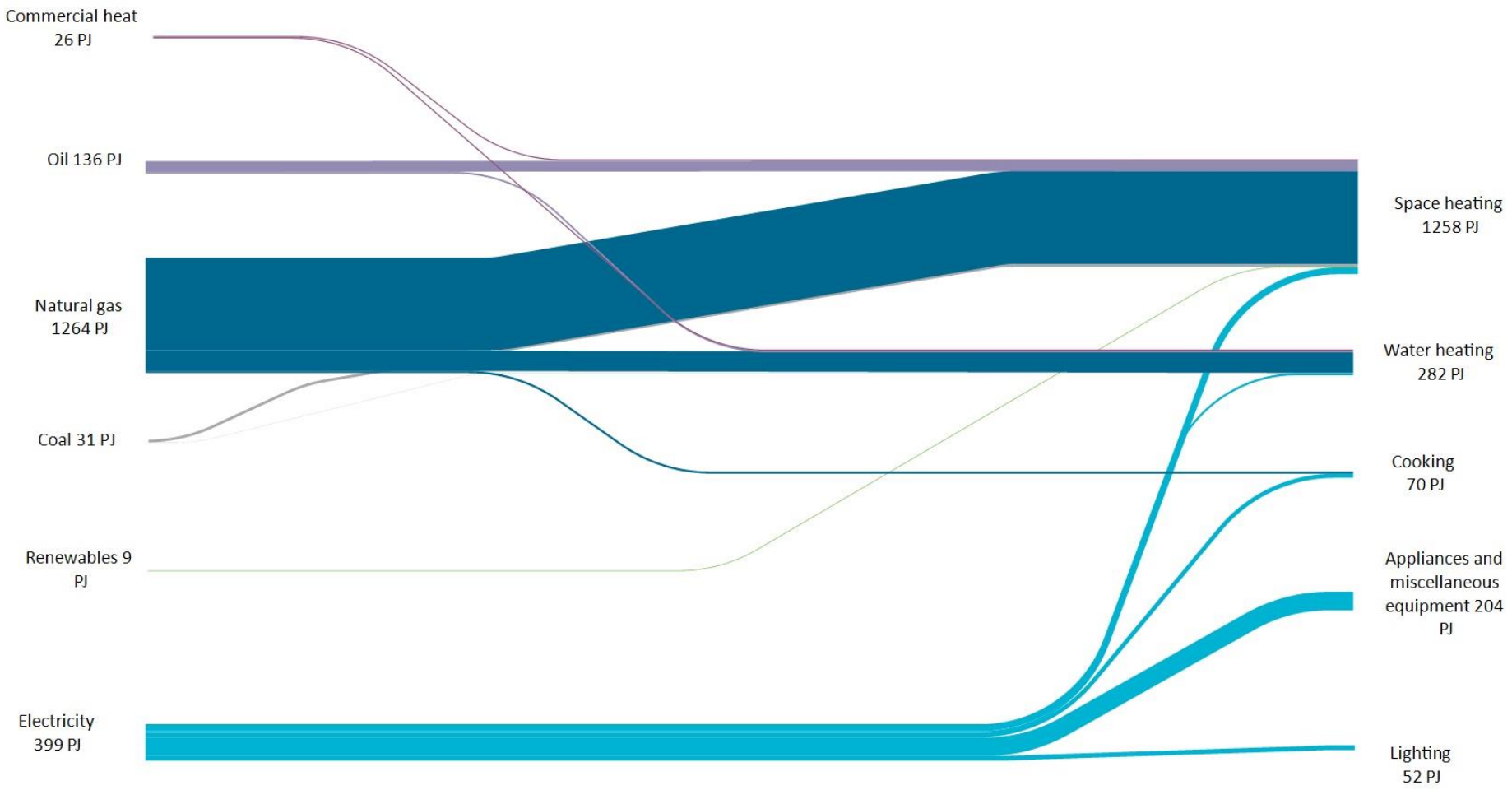
The global picture – heat use in buildings



Ca. 30% of final energy use in the UK – what strategy to decarbonise?



Why behaviour matters here

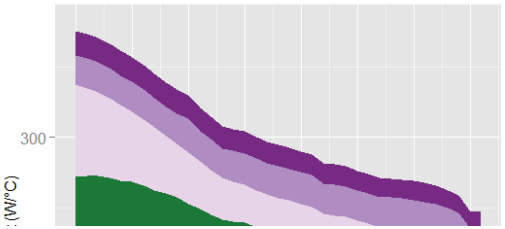
- Retrofit
- Age of stock/physical constraints
- Heterogeneity (stock, market, techs)
- Heat grade/thermal comfort
- Low carbon solutions (and policies) untested

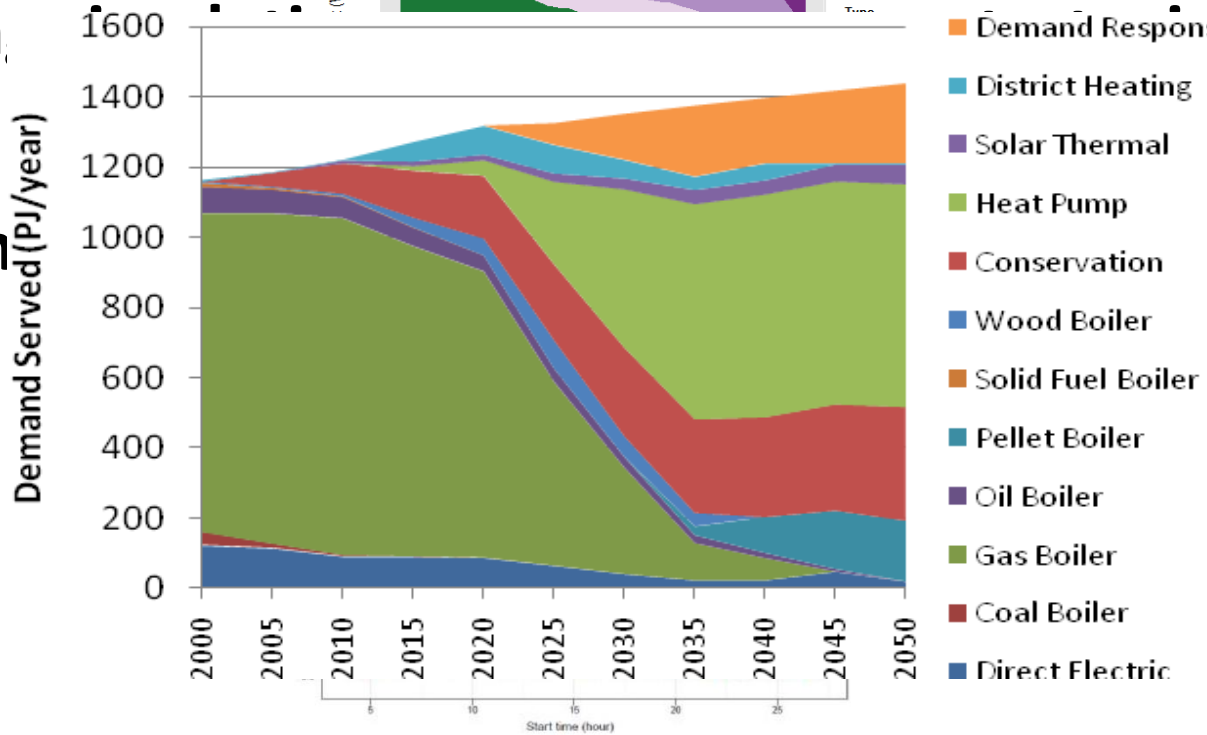
Why look at making energy planning tools better -

- Widely used tools for policy support
- Traditionally based on least-cost modelling approaches:
  - Objective function
  - Decision variables – adoption and use
  - Constraints
- Technology-rich, perfect foresight, perfect markets…
  - Legacy from a different era
- …but for emerging (and most) policy questions it's critical to model non-cost behaviour well

Typical policy support tools in use

- Building sector models – rich representation of the residential sector, not great for strategy
- Energy system m ntation of consumers, resid s
- Buildin analysis
- Agent-
- Econon





Key behavioral parameters – and how modellers usually approach these

- Hidden or intangible costs – add a term to the objective function
- High time-preference for money – high hurdle rate for adoption
- Different sensitivity from different social group
- Distress and other purchasing behaviour – natural and accelerated replacement rates
- Price sensitivity – elasticities

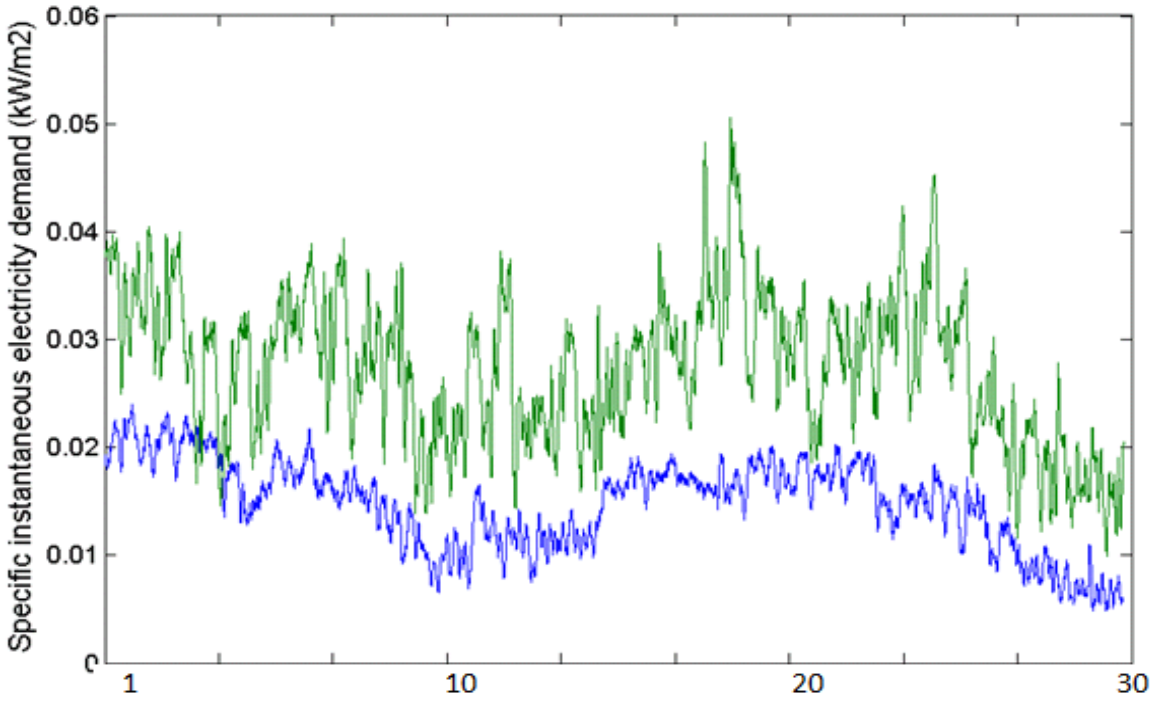
On technology adoption - Modelling Preferences

- Stated preference surveys – strong biases
- Revealed preferences
  - The preferences of consumers/industry can be revealed by their behaviour
  - Can be used to reveal hurdle rates, construct distributions
- Basis in utility maximisation, where technique attempts to quantify the utility function of consumers
- Hedonic Regression

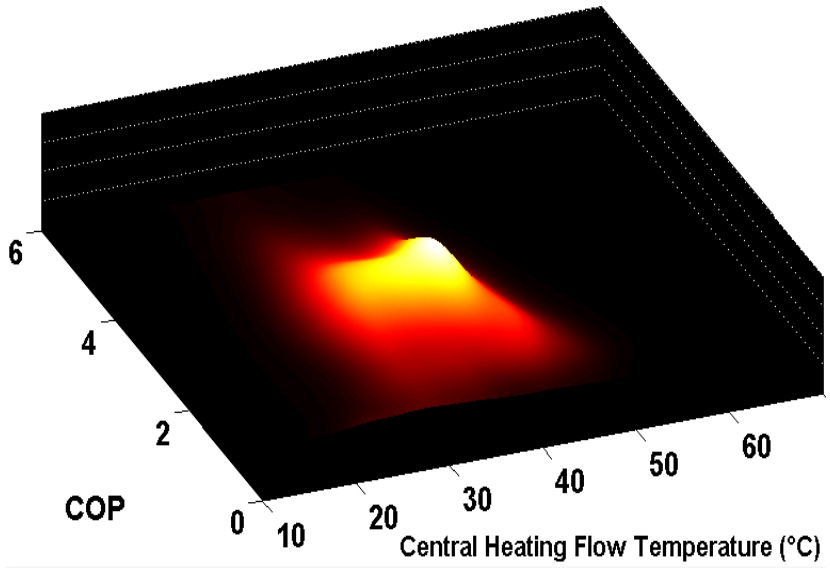
On technology use - new, emerging data sources offer key opportunities

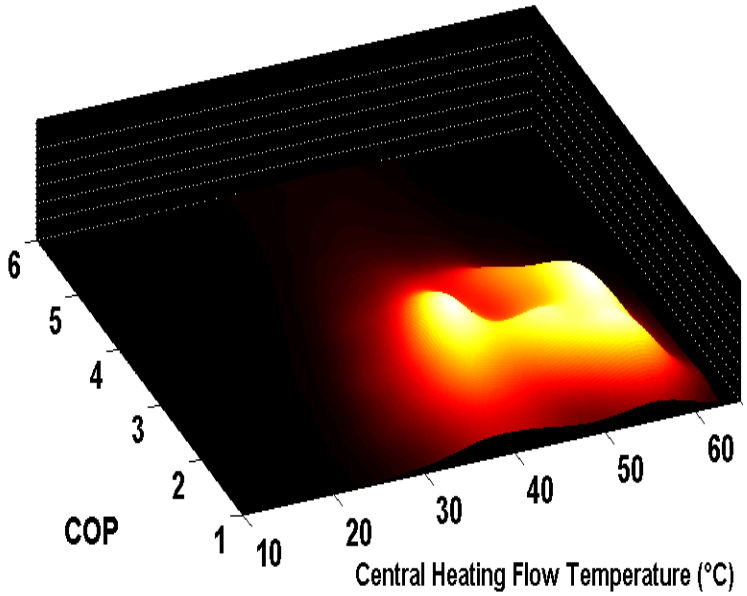
- Real-world data before/after intervention – AMI, field trials, other monitoring
- Demand response programmes
- NEED-style datasets! Econometric analysis of combined impacts of interventions, rebound effects
- Highly powerful – but who should own?

Data from AMI, field trials – heat pumps, boilers, micro-CHP, solar thermal, some types of insulation

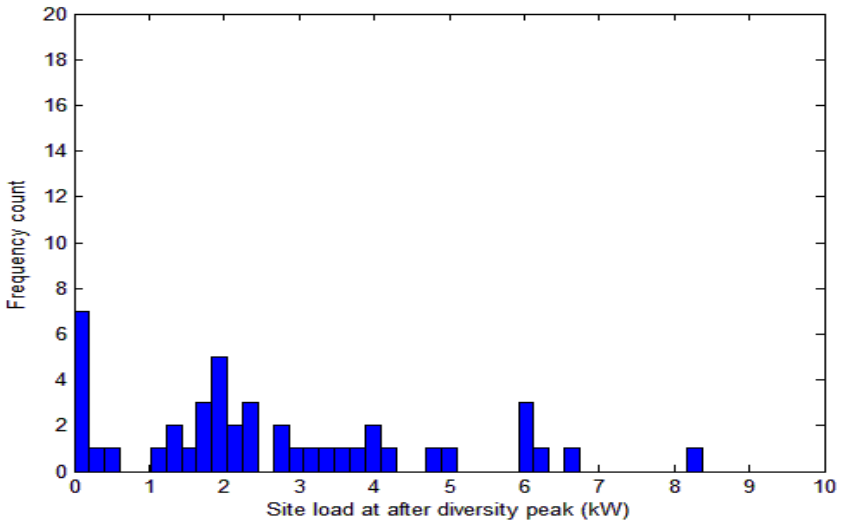


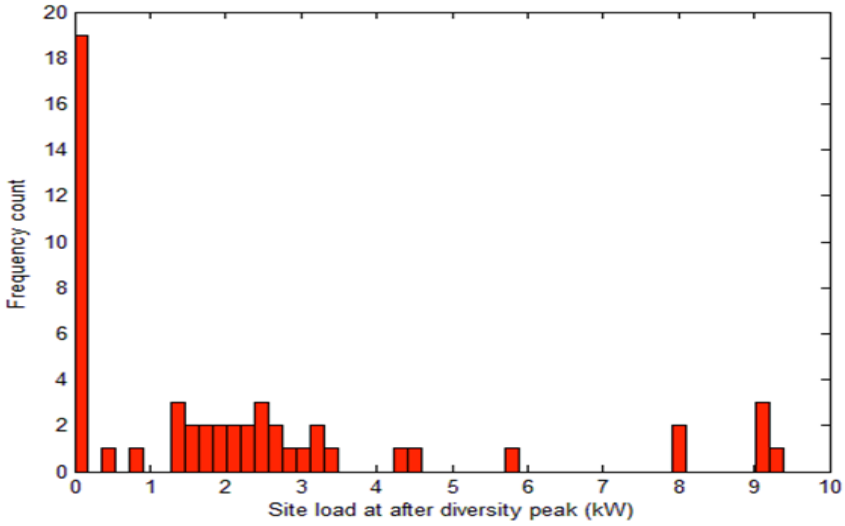
Heat pumps and thermal comfort





Heat storage and load shifting potential





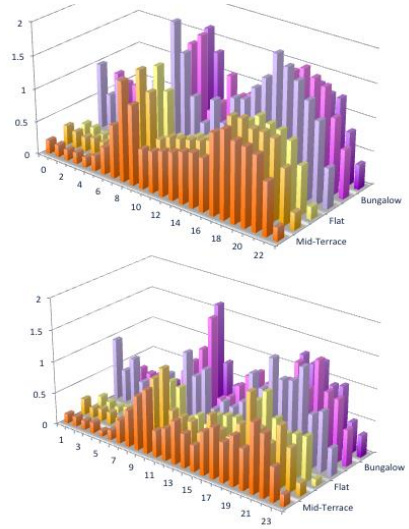
Brief description of approach

- Model 3 different approaches to behaviour
- Spatially explicit, infrastructure and technology-rich* representation of real-world systems
- Integer framework – model every individual intervention on each housing segment and impact on supply
  - Possible to assess impact of a combination of measures (e.g. as data availability progresses - many measures not additive)
- Time- and load-shifting limited by empirical data
- Build-up constrained based on revealed preferences

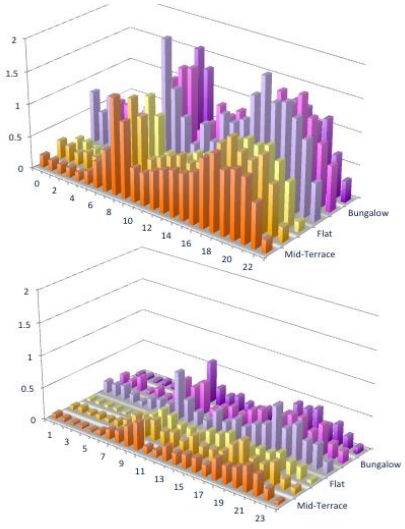
Time domain:
Hourly temporal representation of service demands

Spatial domain:
Explicit characterisation of housing stock, current level of adoption, maximum 'physical' bounds by archetype

Peak

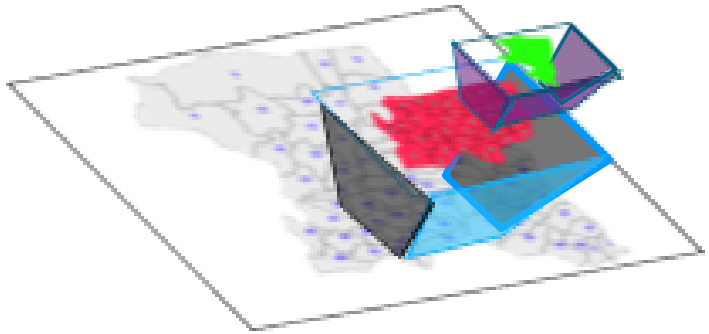


Winter



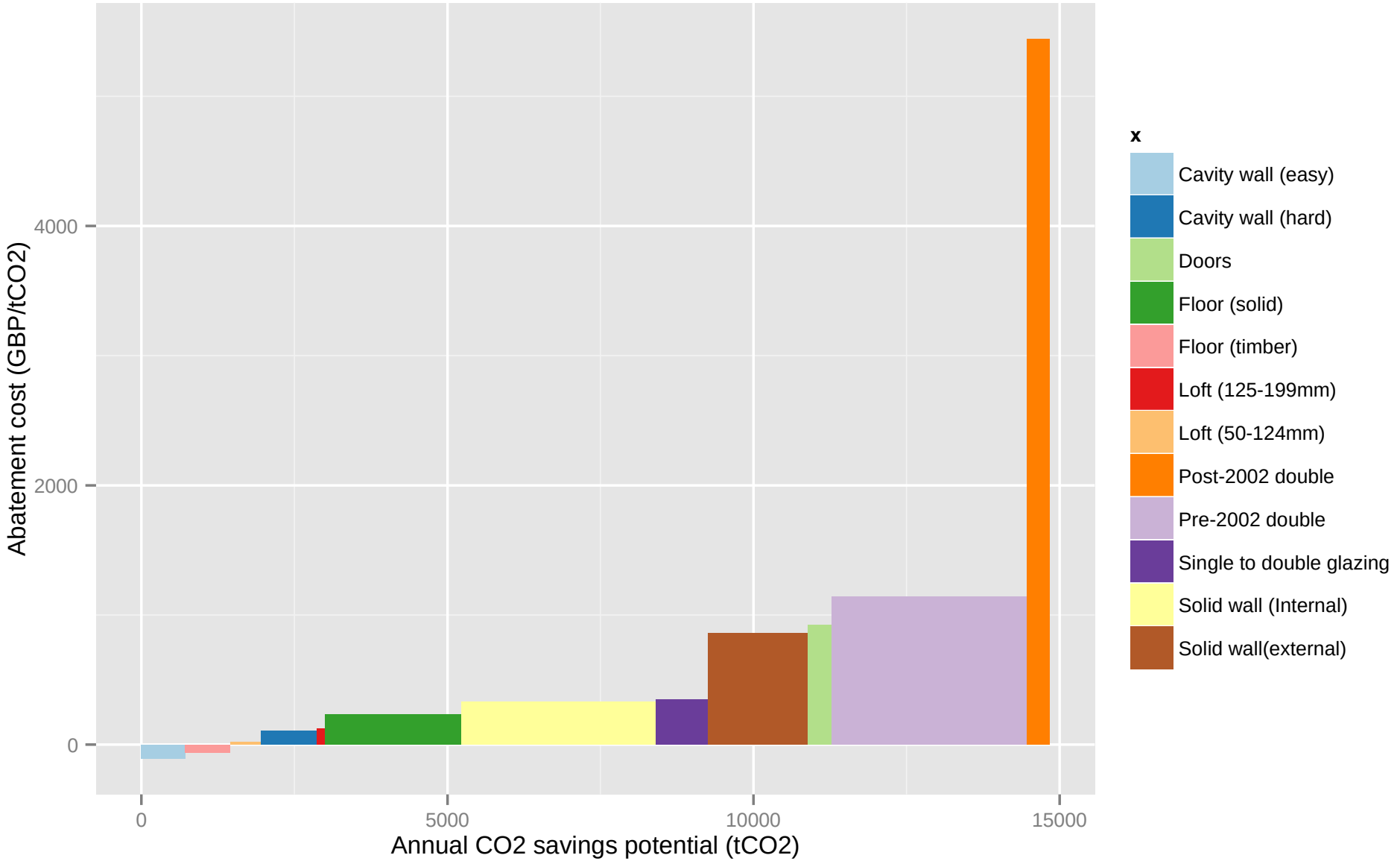
Mid-Season

Summer

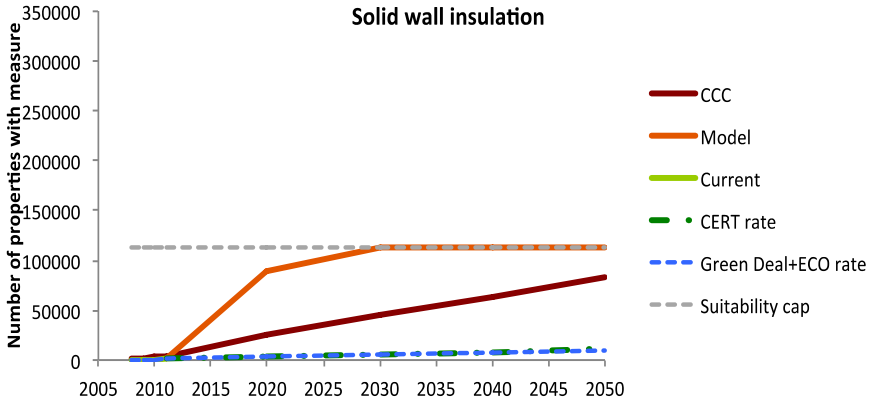


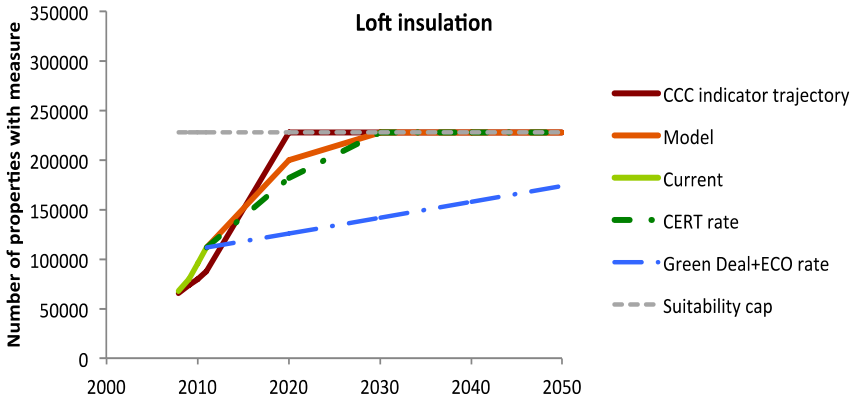
+ simple thermal comfort model

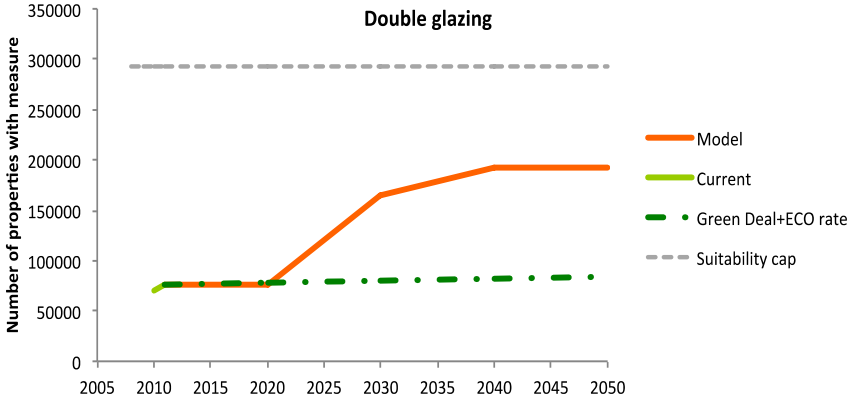
Zones with real-world intervention data

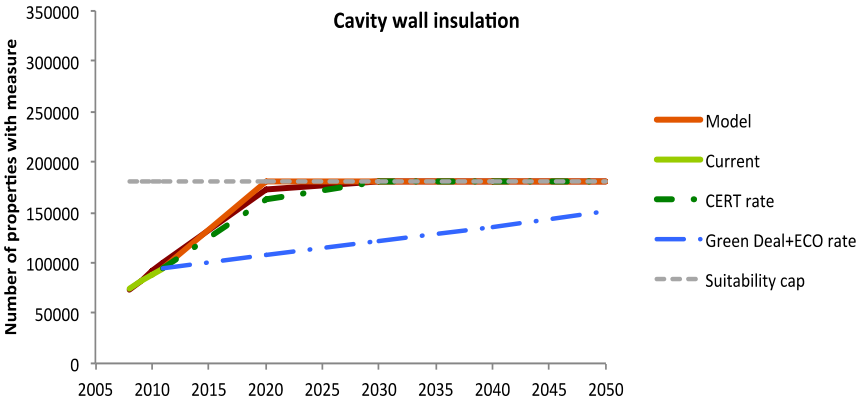


Integer framework to track deployment in each scenario



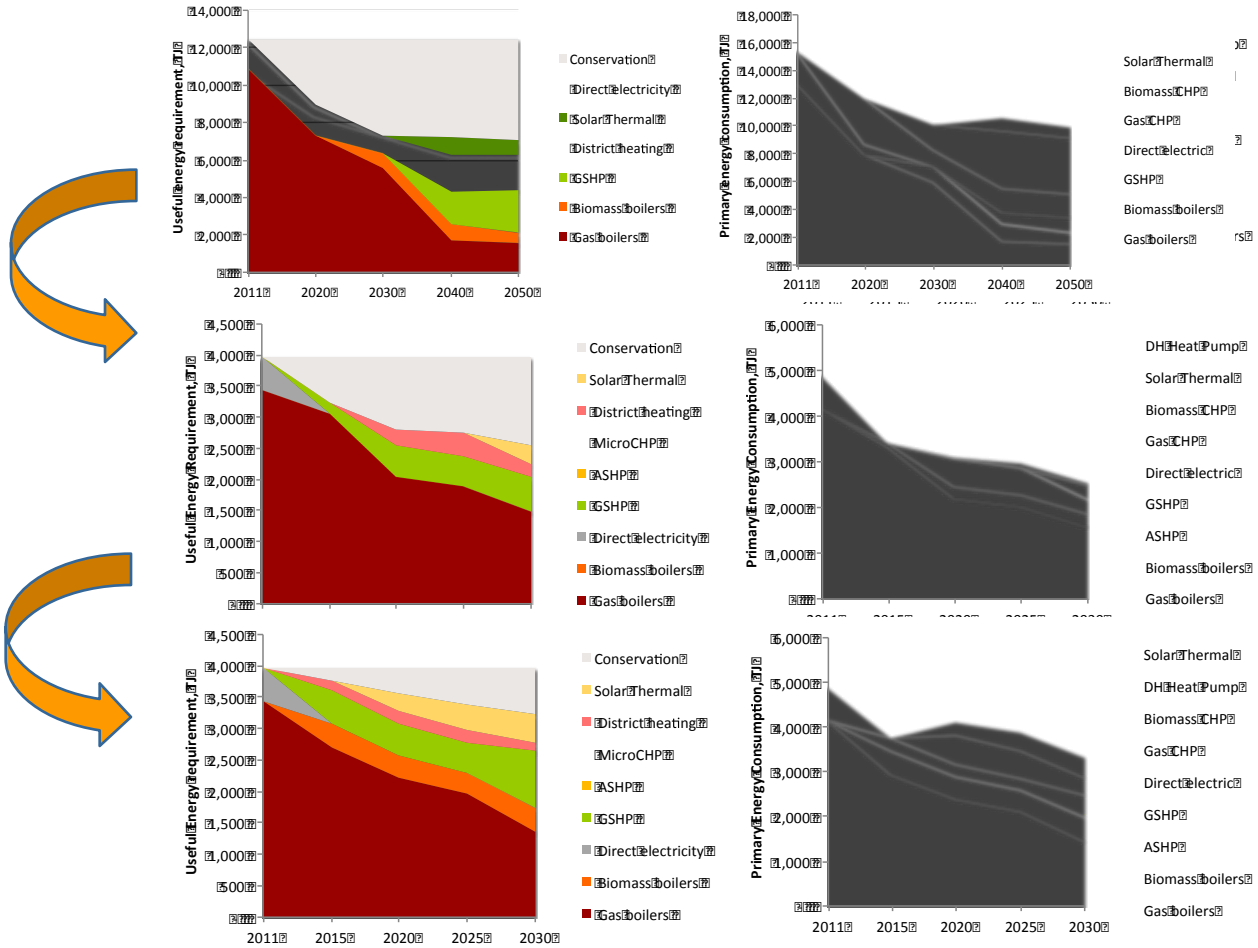






CCC consistently revising assumptions on build-up rates, but no link to formal modelling

- Solid, cavity wall insulation indicators
- HP adoption rates (FE)



‘Big data’ has big value - but how to model more fundamental, radical behavioral change prospectively?

TBC: Smart grids roadmap

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Thank you