Scenario-based modelling of residential energy demand using activity-based approach

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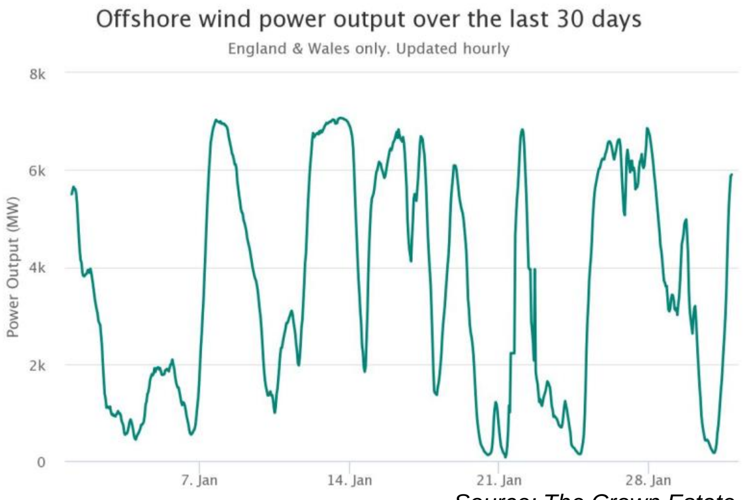
Outline

- Background & rationale
- Objectives
- Activity-based Energy Demand Simulator
- Methodology for scenario-based uncertainty analysis
- Results
- Conclusions

Background & rationale (1)

- The ongoing shift towards use of renewable energy sources has made energy supply volatile, due to dependence on inherently dynamic phenomena, such as wind or sunlight.
- This volatility in supply is nowadays compounded with uncertainty concerning the demand, due to variation in activity participation and the consequent requirements for energy.



Source: The Crown Estate

Background & rationale (2)

- But uncertainty is costly:
  - requires enough generation and/or transmission capacity to accommodate (uncertain) peaks in demand
  - requires an ongoing management of the infrastructure, increasingly challenging due to de-centralisation in not only consumption but also generation and storage
  - requires presence of appropriate measures to quickly re-balance the network
- This implies the need for not only a high resolution demand prediction but also the associated uncertainty.
- Moreover, only de-composition of this uncertainty provides a means towards understanding the extent to which it is amenable to reduction

Objectives

- To propose an approach that utilises a high-resolution activity-based agent demand simulator as a means of decomposing the sources of uncertainty in energy demand through a scenario-based uncertainty analysis
- To demonstrate how uncertainty can be reduced via behavioural coordination, using the example of coordinated work-from-home adoption

Agent- and activity-based microsimulation model (1)

- Stemming from the need to move away from aggregate representation of the demand for energy, in the wake of an increasingly decentralised considerations in the energy sector:
  - EV (dis)charging decisions, demand side response, local generation & storage
- Guiding principles behind the current version:
  - Agent-based ➔ Representations of agents (people) and their households
  - Activity-based ➔ Agents undertaking activities.
  - Focus on energy-related applications ➔ EVs and appliances. Elasticities.
  - Low-barrier for experimentation ➔ implementation in R

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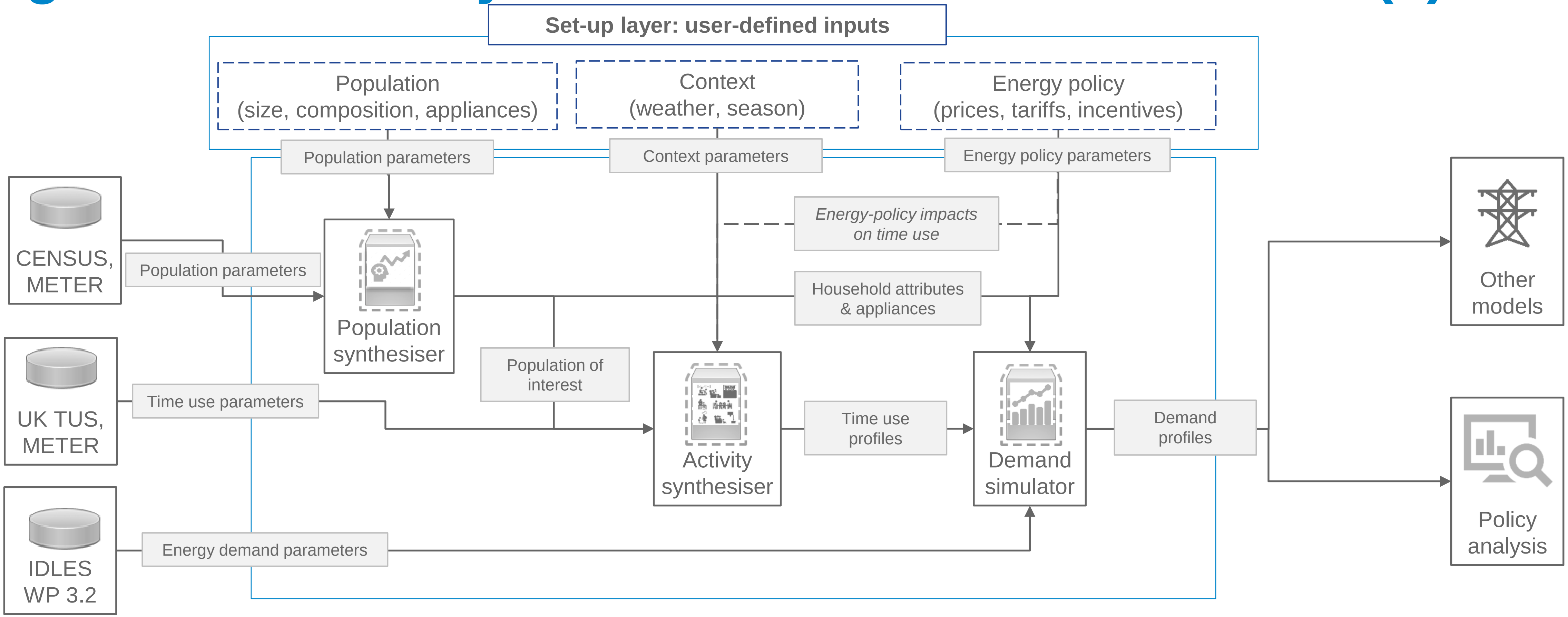
Agent- and activity-based microsimulation model (2)



Agent- and activity-based microsimulation model (3)

- The simulation frameworks consisting of 3 core components:
  - **(1) Population synthesiser** creates a digital representation of the population following the desired properties (sociodemographic, vehicle and appliance ownership, etc.)
    - Draws from the UK Time Use Survey 2014-15, modified in a desired way to meet the distributional assumptions, e.g. EV ownership levels
  - **(2) Activity synthesiser** assigns suitable time use patterns to the households and individuals, consistent with day of the week, household attributes, etc.
    - Draws from the UK Time Use Survey 2014-15, with activities modified to implement time-use oriented policies, such as work from home.

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Agent- and activity-based microsimulation model (4)

- Cont.
  - **(3) Energy demand simulator** produces energy (electricity, given the available data) demand profile for 24 hours, taking into account:
    - Agent and household attributes
    - Agent activities undertaken at home
    - Energy prices (up to 1-min level disaggregation possible)
    - Weather
    - EV usage pattern
  - The model incorporating activities based on a log-linear, household-level model calibrated using Project METER data
    - The model can also produce marginal changes to electricity consumption due to participation in an activity

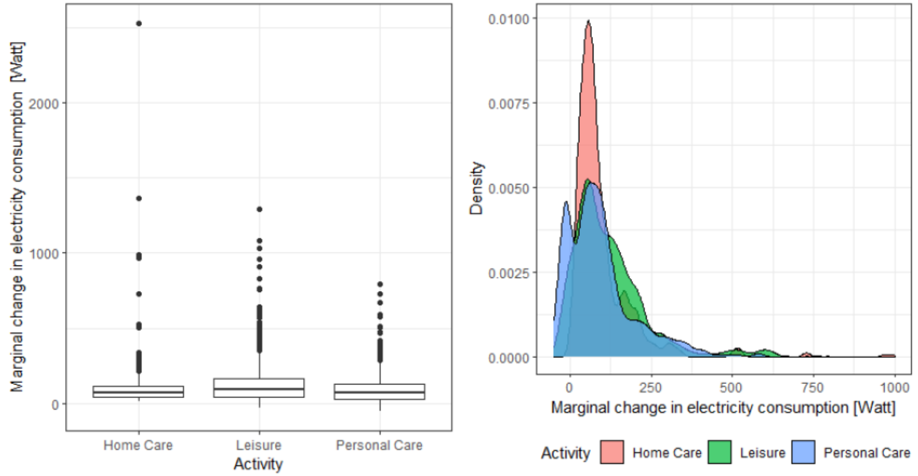


Figure 4 Estimated marginal change in electricity consumption due to the activity undertaken in the household for home care, leisure and personal care activities

Ref: Pawlak, J., Imani, A.F. and Sivakumar, A., 2021. How do household activities drive electricity demand? Applying activity-based modelling in the context of the United Kingdom. Energy Research & Social Science, 82, p.102318.

Methodology (1)

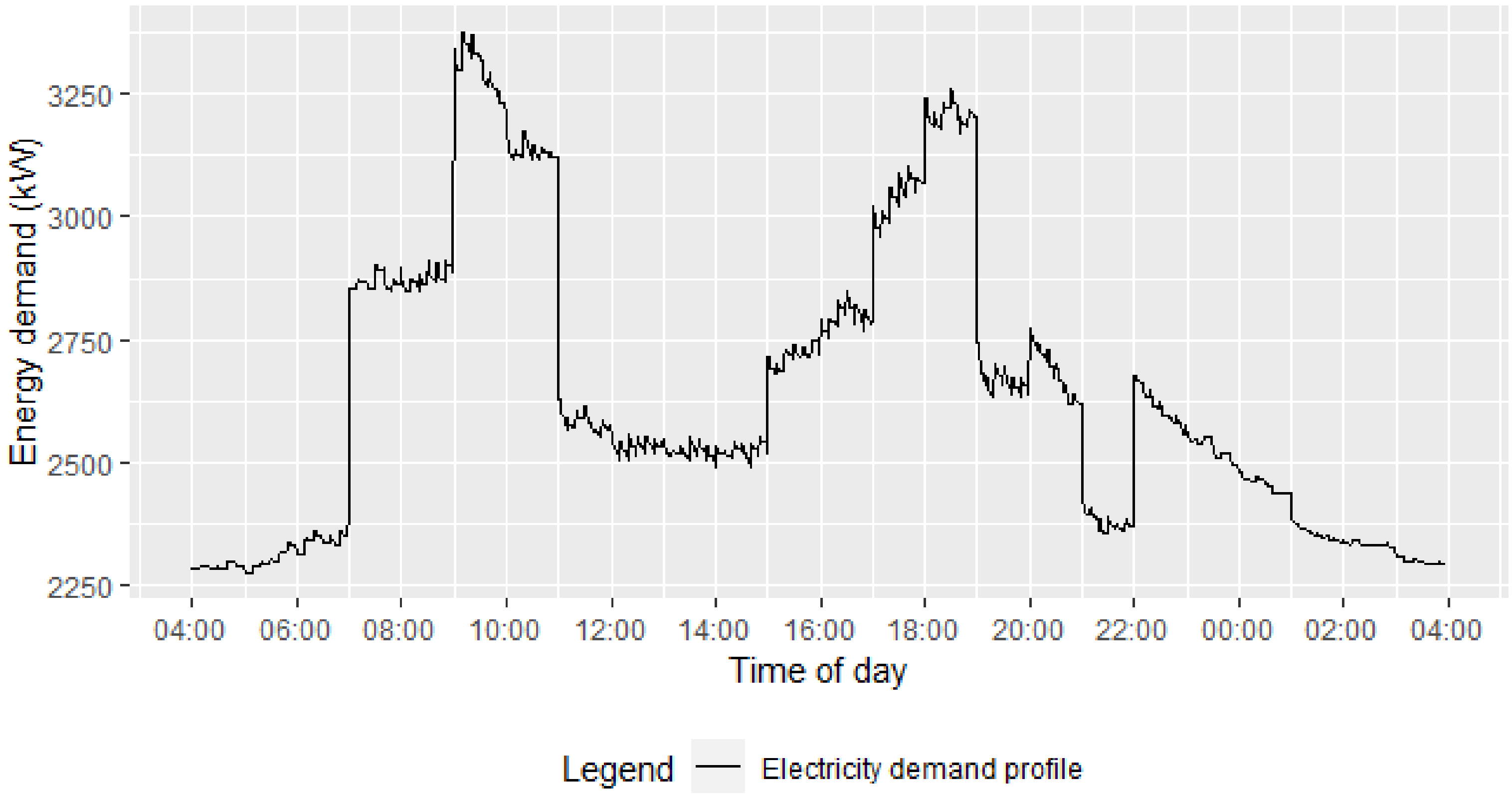
- We assume the following sources of uncertainty, which can be accounted for in the model:
  - Behavioural: endogenous to the consumers
    - e.g. variations in activity-travel behaviour
  - Exogenous: fundamentally stochastic and exogenous to the consumers
    - e.g. weather, conditions on transport network
  - Model: resulting from the assumptions concerning the model structure as well as sample-based nature of the model parameters
    - e.g. assumed model structure, estimated model coefficients and standard errors

Methodology (2)

- Create a number of scenarios: 27 scenarios
  - Point estimate for a single run
  - Mid-point and max/min demand with variation in activities (3)
  - Mid-point and max/min demand with variation in activities and weather (3 x 3)
  - Mid-point and max/min estimate with variation in activities, weather and selected parameters
- Derive range for the above, resulting in contribution to uncertainty
- 3 scenarios to showcase reduction in uncertainty
  - Coordinated WFH – reduce uncertainty from activities
    - Calculate difference in the uncertainty between **Coordinated WFH and do nothing**
    - Value at price of battery storage – total and per household
  - V2G proliferation ... How to model this??
    - Remove EV loads – perfect balance between charging and discharging ??
  - Improved forecasting
    - Behavioural – activities, weather, model components
    - Value at price of battery storage

Results (1)

- Start with a baseline simulation setting:
  - 24 hours
  - 750 households
  - A random weekday in May



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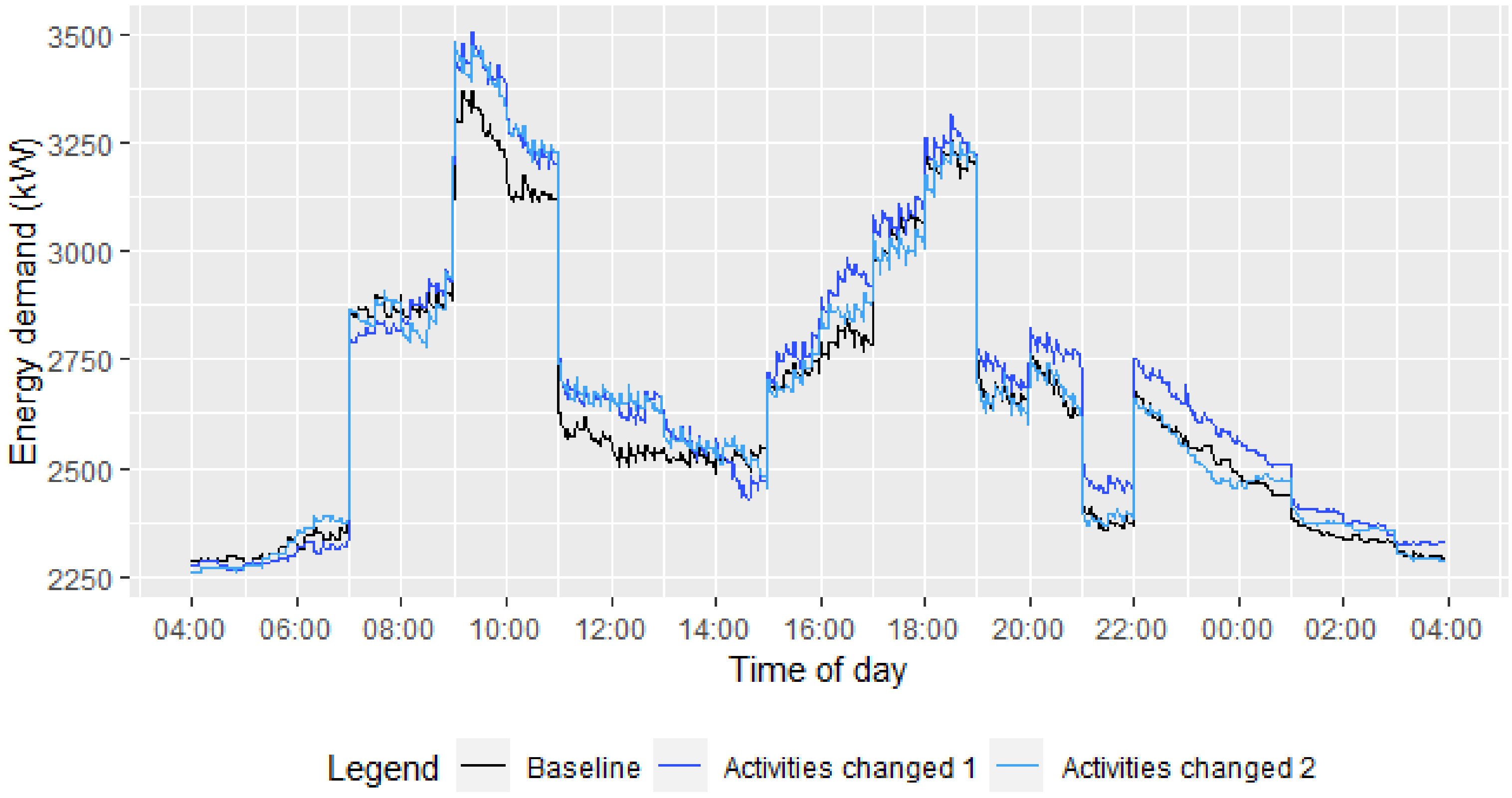
Results (2)

- Adding variation in **activities** of the same households
- Uncertainty (absolute):

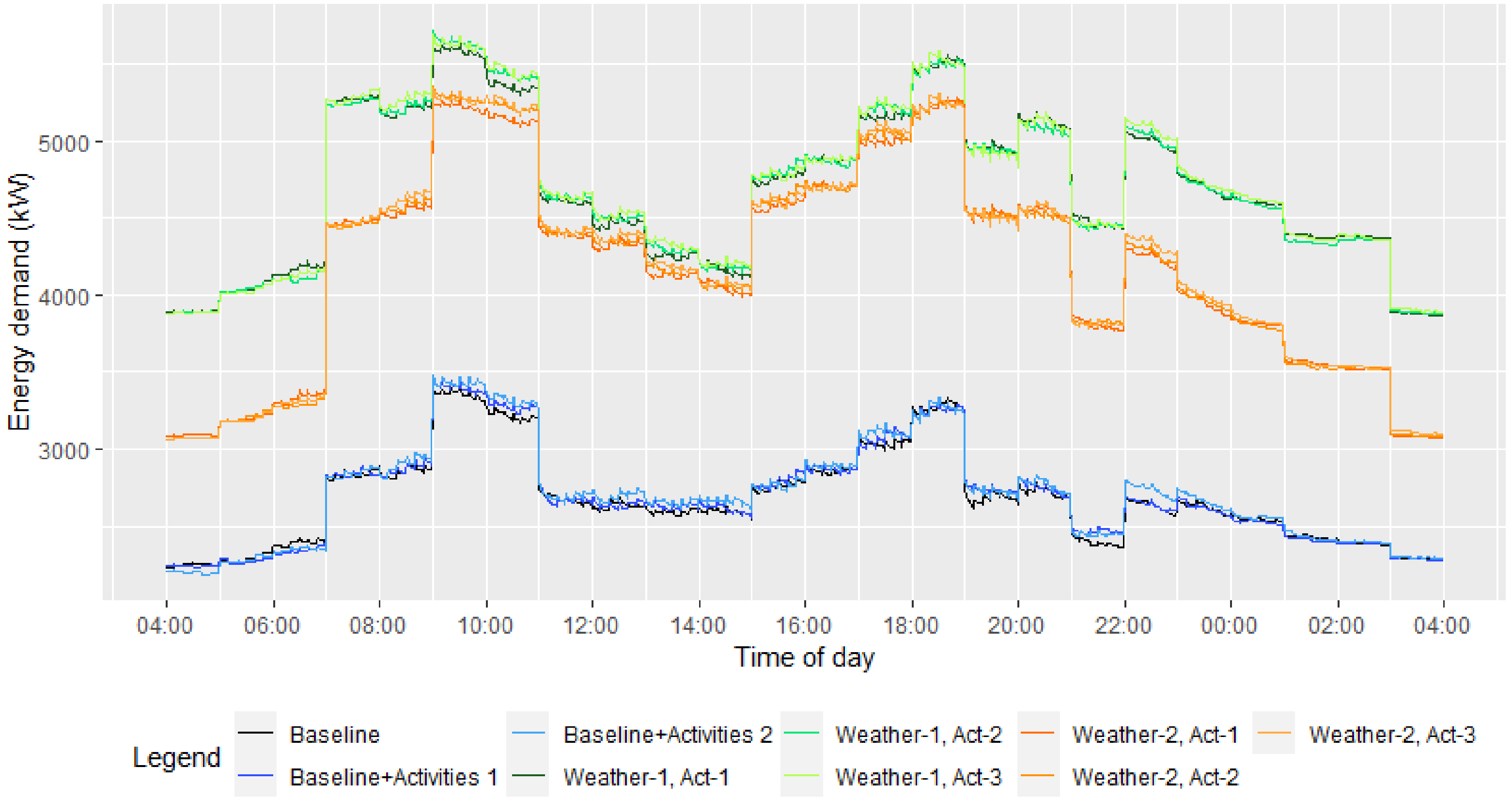
in kW	Sample	Per HH
Max.	37.360	0.245
Mean	73.416	0.098
Min.	4.202	0.005
Std. dev.	37.357	0.050



Results (3)

- Adding further variation in **weather**
- Uncertainty (absolute):

in kW	Sample	Per HH
Max.	2502.766	3.337
Mean	2065.443	2.754
Min.	1597.418	2.130
Std. dev.	256.619	0.342



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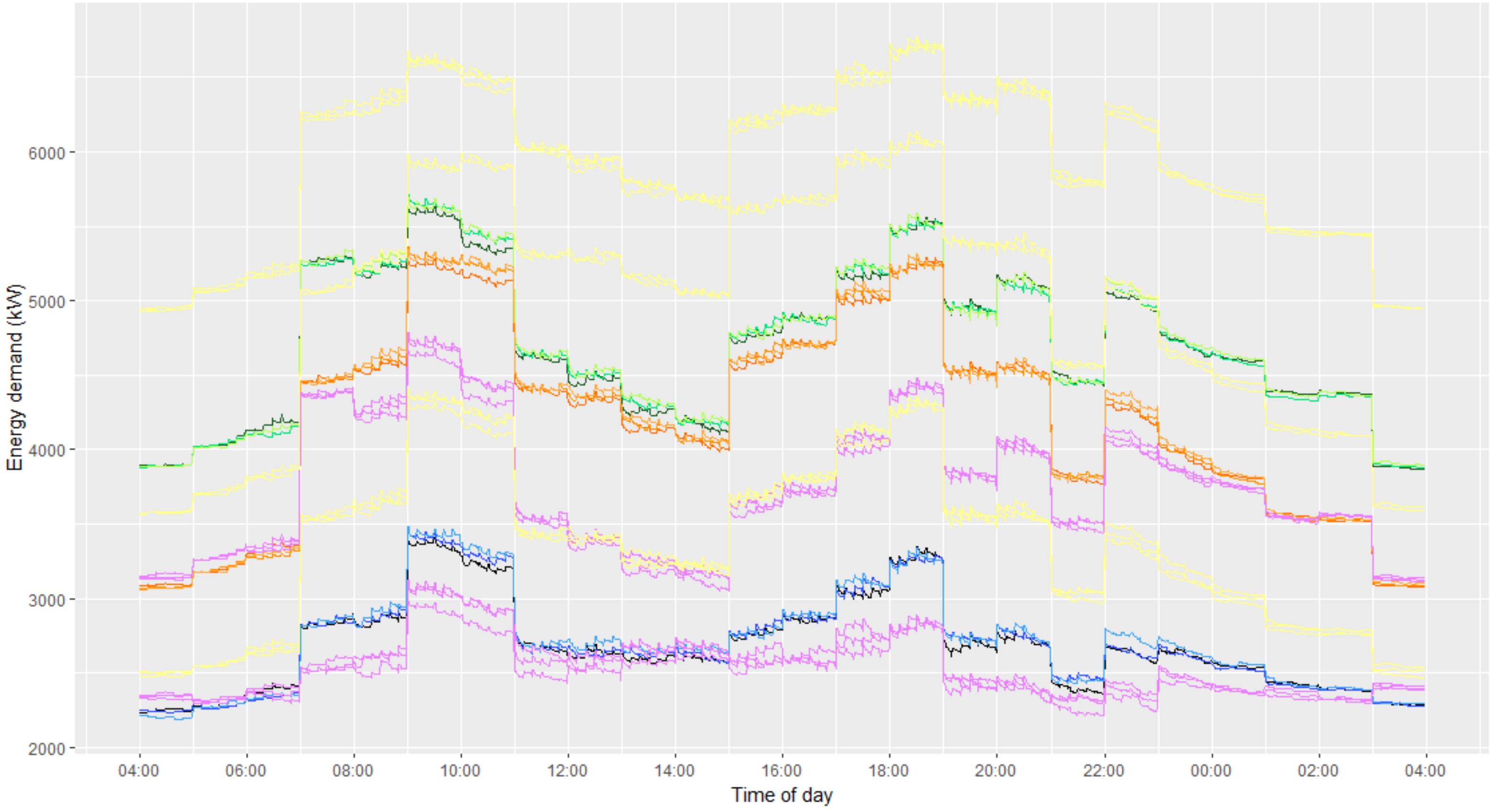
Results (4)

- Adding further **coefficient** uncertainty (work and temperature)
- Uncertainty (absolute):

in kW	Sample	Per HH
Max.	4100.841	5.468
Mean	3473.369	4.631
Min.	2666.980	3.556
Std. dev.	408.352	0.544



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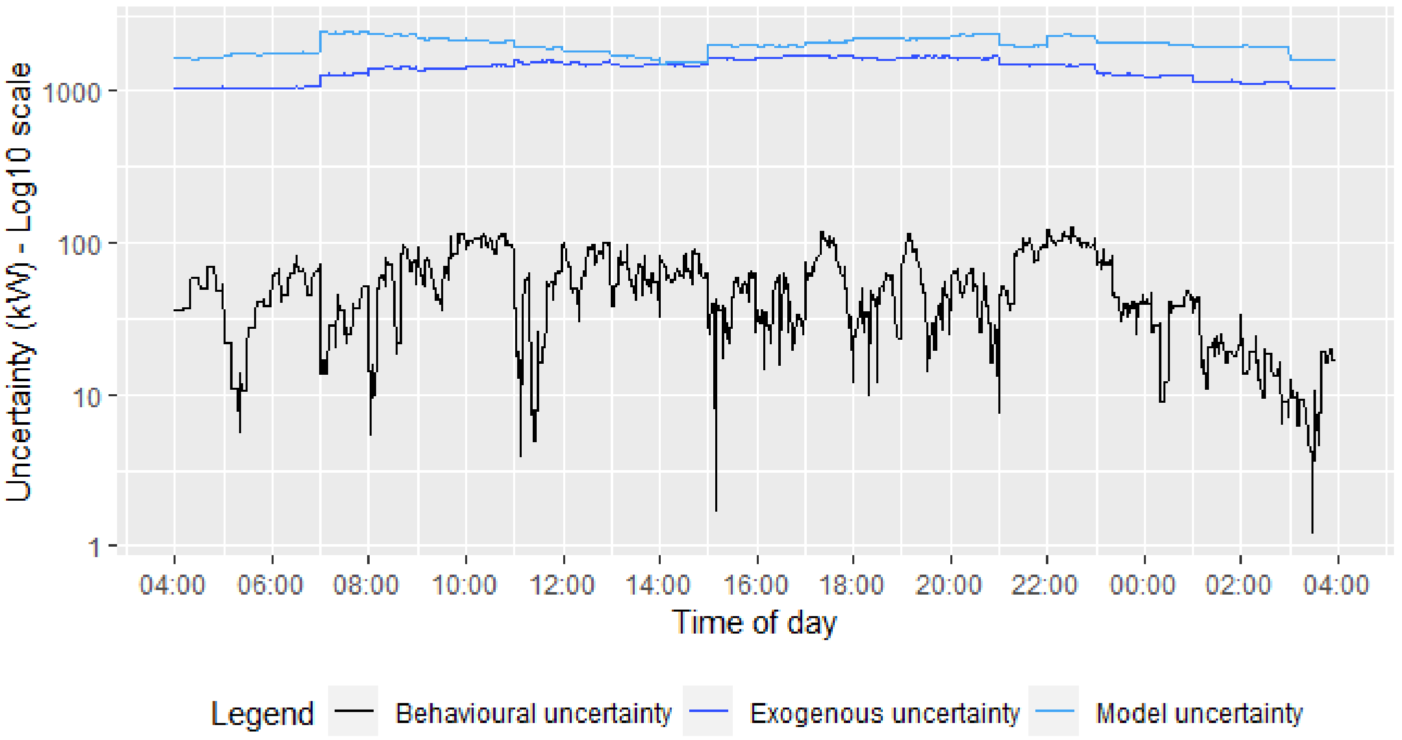
Results (5)

- We can now decompose the sources of uncertainty

in kW	Min.	Mean	Max.
Behavioural	0.04%	1.49%	3.24%
Exogenous	49.12%	58.05%	65.24%
Model	33.85%	40.47%	48.55%



Scenario analysis: WFH to reduce behavioural uncert. (1)

- What can we do about the different sources of uncertainty?
- Improved modelling (always) – reduces uncertainty, but **not** the variation
  - Exogenous uncertainty – improved weather forecasting
  - Model uncertainty – better data and structures
  - Behavioural – better behavioural models and data (note: privacy!)
- Uniquely for the behavioural uncertainty, we can try and reduce it via coordination & planning
- We will demonstrate this using an example of coordination in work-from-home policy

Scenario analysis: WFH to reduce behavioural uncert. (2)

- Our previous work looked at employing the demand simulator to assess impacts of WFH policies on electricity demand*
- Our findings, using synthetic population, indicated that implementation of teleworking policies leads to about 2–5% higher demand in residential electricity on average. This is much lower than the impact of EV uptake and the consequent increase in electricity demand.
- We are now looking at the scenario where WFH is adpopted by the residents

*Ref: Trask, A. et al., 2021. Impacts of COVID-19 on the Energy System. Energy Futures Lab White Paper, EFL, Imperial College London.

Scenario analysis: WFH to reduce behavioural uncert. (3)

- Baseline

in kW	Sample	Per HH
Max.	37.360	0.245
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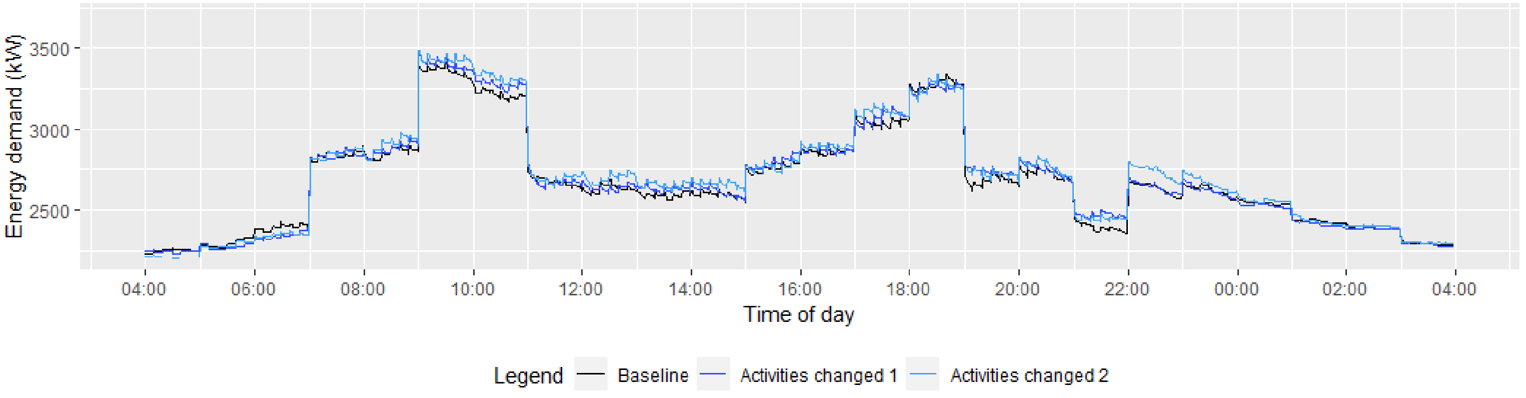
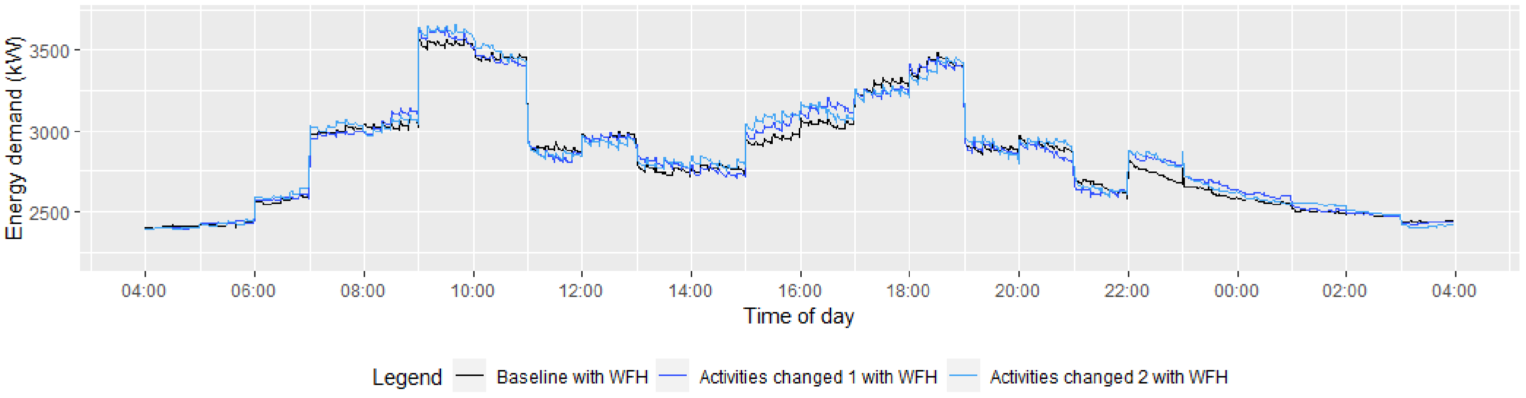
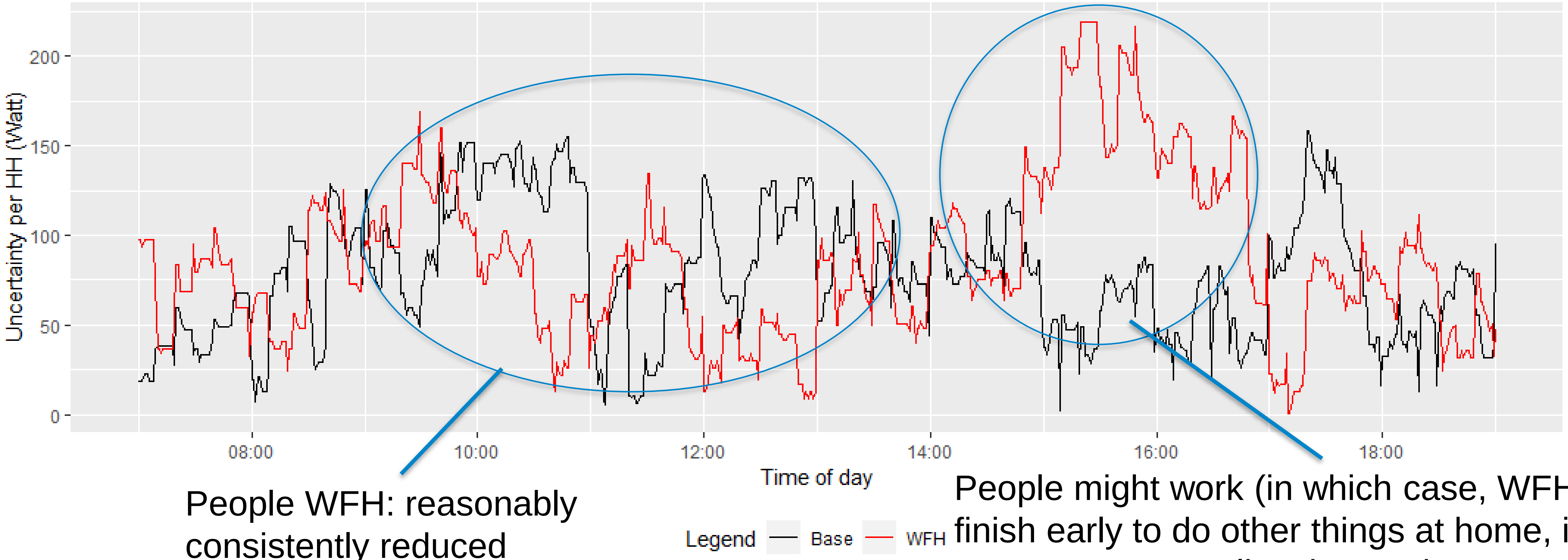


- WFH

in kW	Sample	Per HH
Max.	156.941	0.209
Mean	52.642	0.070
Min.	0.339	0.002
Std. dev.	31.700	0.039



Scenario analysis: WFH to reduce behavioural uncert. (4)



People WFH: reasonably consistently reduced uncertainty

People might work (in which case, WFH) or finish early to do other things at home, in which case no WFH applies, increasing uncertainty

Conclusions

- We have demonstrated how activity-based agent demand simulator can be used to decompose uncertainty in the demand resulting from:
  - Uncertainty in agent behaviour
  - Exogenous uncertainty
  - Model-related uncertainty
- In the current setting, exogenous uncertainty was found to be the largest (due to unpredictable weather), followed by model uncertainty and behavioural
- We have shown the example of how WFH can be used to reduce behavioural uncertainty, although the effect is somewhat complex and not that large in magnitude

Further directions of inquiry

- Modelling the value of uncertainty reduction in the presented context
- Exploration of extreme-events scenario: combination of parameters that lead to extremely high/low demand
- Design and testing of uncertainty-reducing policies
  - Coordination in activities
  - Coordination in EV (dis)charging
  - Neighbourhood-level coordination in local generation and consumption
- Design of win-win arrangements, where reduction in uncertainty is the primary source of value

Thank you!

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