Uncertainty, Opportunities and Risk for 21st Century Energy Systems

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Power is a sector in constant transformation:
Electricity and downstream gas prime examples

Source: Tony Ward, EY

Definitions

- **Risk** is the deviation of an actual future outcome relative to the expected outcome.

- **Uncertainty** refers to the unpredictability of possible future outcomes.

"*Risk has an unknown outcome, but we know what the underlying outcome distribution looks like. Uncertainty also implies an unknown outcome, but we don't know what the underlying distribution looks like*."

Source: Knight, F. H. (1921). *Risk, uncertainty, and profit*. Boston: Hart, Schaffner & Marx, Houghton Mifflin Company.

Modelling and Uncertainty

Uncertainty is a key issue in integrated modelling because:

- Integrated models can cover a wide variety of domains, each with uncertainties arising from a range of different types and sources.

- Integrated models are designed to capture a wide range of cause–effect relationships in a specific problem domain. Thus, they tend to accumulate uncertainties.

A Taxonomy of Uncertainty

Uncertainty can arise due to (a):

Variability/randomness (aleatory uncertainty)

The system under consideration can behave in different ways in different places and times due to *inherent randomness (envrionmental stochasticity, human behaviour, societal randomness*, *technological surprises*..*)*. *Called.*

A Taxonomy of Uncertainty

Uncertainty can also arise due to (b):

Lack of knowledge (epistemic uncertainty)

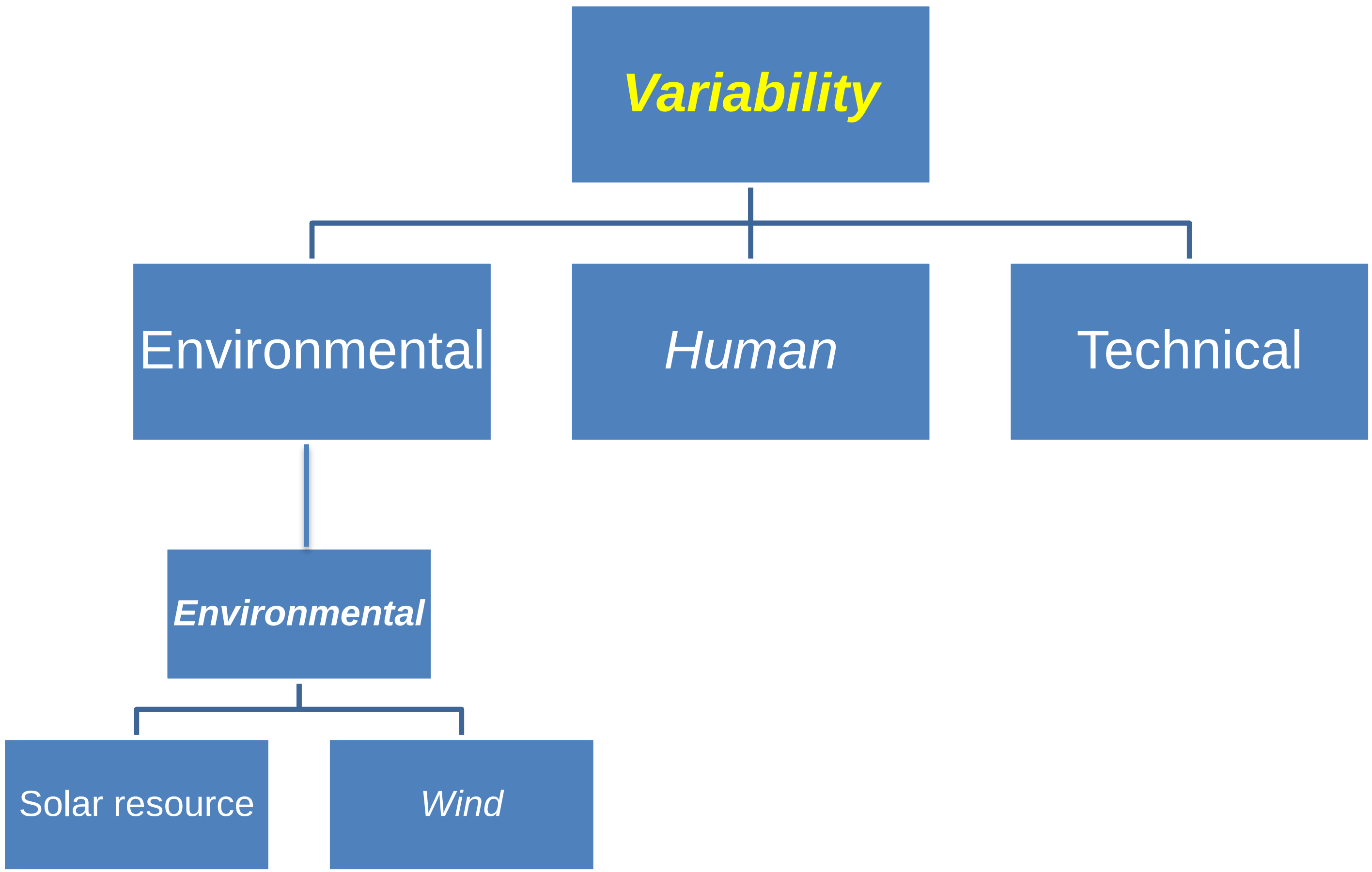
For example, knowledge of deterministic processes and how to model them can be incomplete.

There are different kinds of lack of knowledge, ranging from:

1. *Inexactness*
2. *Lack of observations/measurements,*
3. *Difficult to measure*

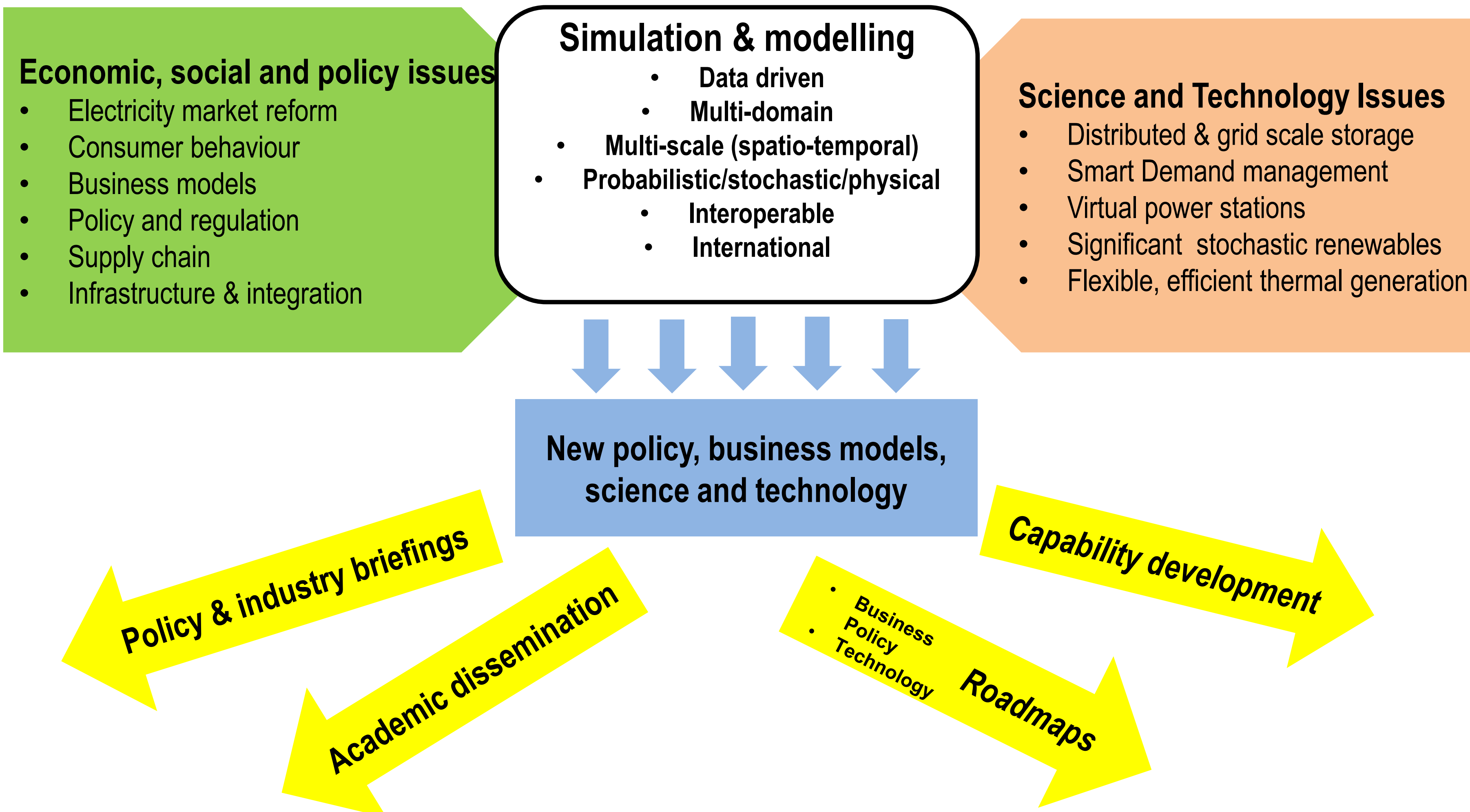
4. *Conflicting evidence*
5. *Ignorance*
6. *Vagueness*

An Uncertainty Taxonomy



Rotmans, Jan, and Marjolein BA van Asselt. *"Uncertainty in integrated assessment modelling: a labyrinthic path." Integrated Assessment* 2.2 (2001): 43-55.

An Integrated Research Approach



Case Study: PV2025 (PV Impact Analysis)

Key questions: Technology

- What are the aspects /difficulties in quantifying PV performance?
- What are suitable locations for installation?
- How well does a system perform?
- Can we predict energy output?
- What are the network impacts?

Key questions: Socio-economic

- What is the return on investment?
- What are the *actual* emission reductions?
- Are there impacts on fuel affordability?
- Are there other socio-economic aspects?

Process for Predicting Solar Array Output

1. Interpolation (kriging) of Met. Office hourly global horizontal irradiation and temperature data – creates a country-wide grid of values.
2. Determine tilt and azimuth of rooftop solar panels from LiDAR and Ordnance Survey building outlines. (Standard tilt/azimuth assumed from solar farms).
3. Separate global horizontal irradiation into beam and diffuse so we can:
4. Translate irradiation onto a tilted plane.
5. Calculate module temperature from plane-of-array irradiance and ambient temperature.
6. Compute output power with electrical model.

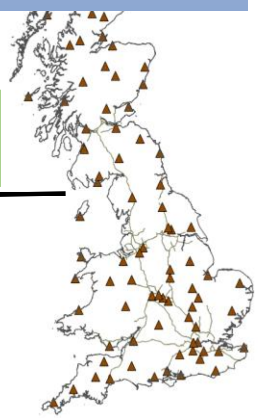
Rowley, P., Leicester, P., Palmer, D., Westacott, P., Candelise, C., Betts, T., & Gottschalg, R. (2014). "Multi-domain analysis of photovoltaic impacts via integrated spatial and probabilistic modelling". Renewable Power Generation, IET, 9(5), 424-431.

Koubli, E., Palmer, D., Rowley, P., & Gottschalg, R. (2016). Inference of missing data in photovoltaic monitoring datasets". IET Renewable Power Generation. (2016).

Calculation of PV Output Data

Start

Kriging of Met. Office Data: 80 weather stations



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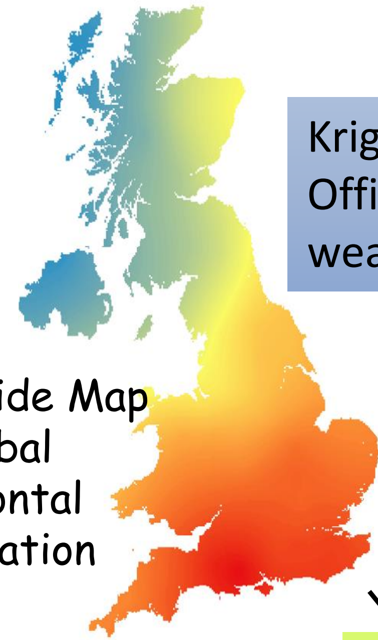
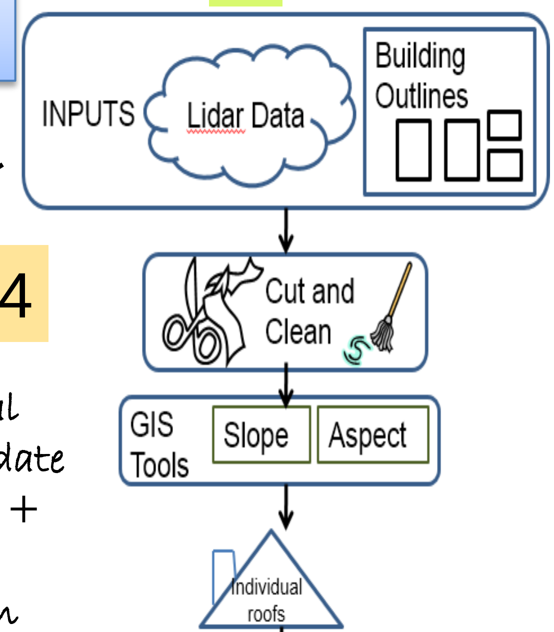


UK-Wide Map of Global Horizontal Irradiation

2



3

Separation: BRL model

4

Translation: Hay &McKay with Reindl's correction

Global Horizontal Irradiance + time/date + lat/long + Tilt + Azimuth = Tilt Irradiation

5

Plane-of-array irradiance for each solar farm/domestic system

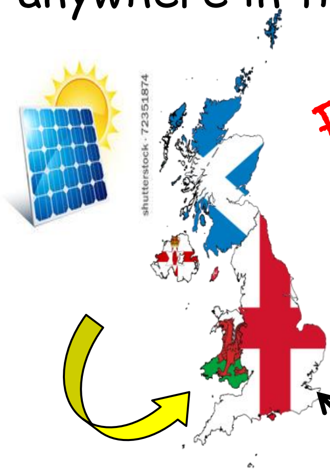
6

King model for the maximum power point P(G,T) with adjusted coefficients

Ross thermal model

Models that take as input irradiance and temperature (the only available information)

Finish



Output for any solar array anywhere in the UK

PV Performance Maps for UK Solar Farms

Research aims to evaluate area-to-area variability of PV performance.

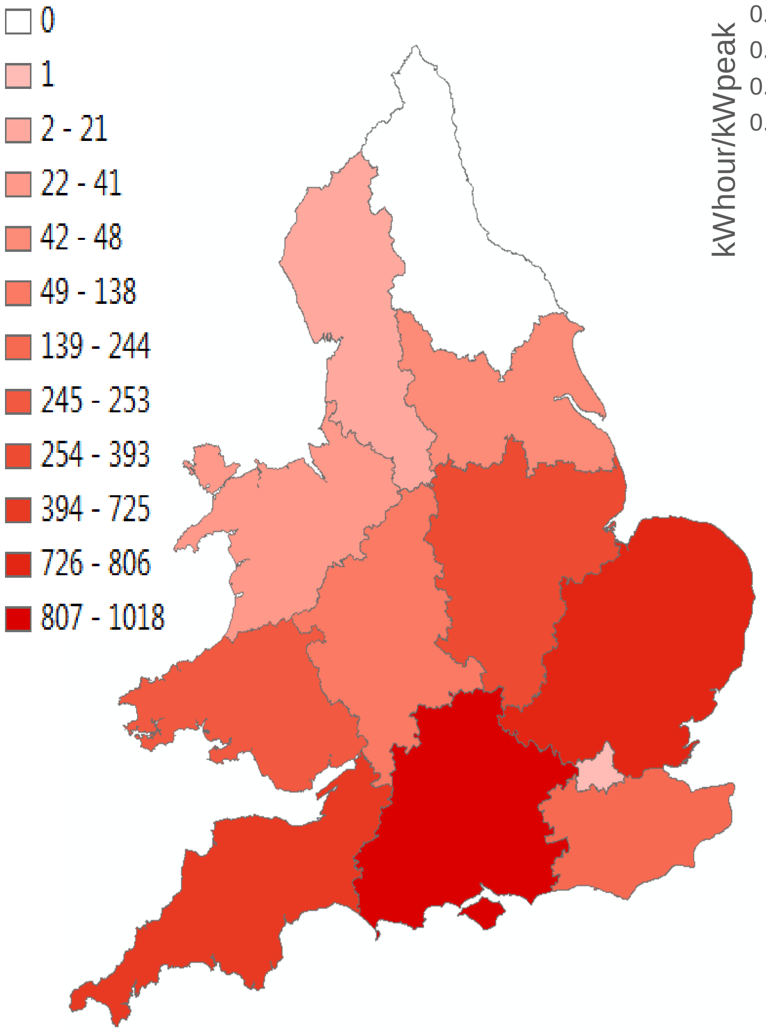
- Southern UK has the highest output due to highest solar resource but results are also influenced depending on whether the study focuses on DNO or grid supply point.
- Average kWh/kWp over ten years was analysed countrywide. Nameplate capacity is seldom reached.
- Output of DNOs in the east of the country peaks at noon, whilst westerly located DNOs maximise at 1pm. The UK average value is highest at 1pm. Eastern DNOs have highest output in the morning and western ones in the afternoon.

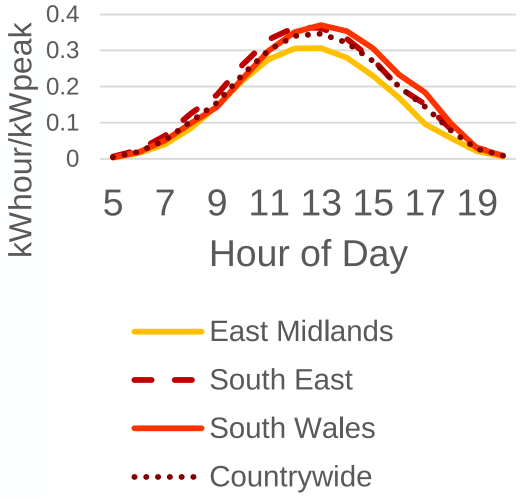
Rowley, P., Leicester, P., Palmer, D., Westacott, P., Candelise, C., Betts, T., & Gottschalg, R. (2014). “Multi-domain analysis of photovoltaic impacts via integrated spatial and probabilistic modelling”. Renewable Power Generation, IET, 9(5), 424-431.

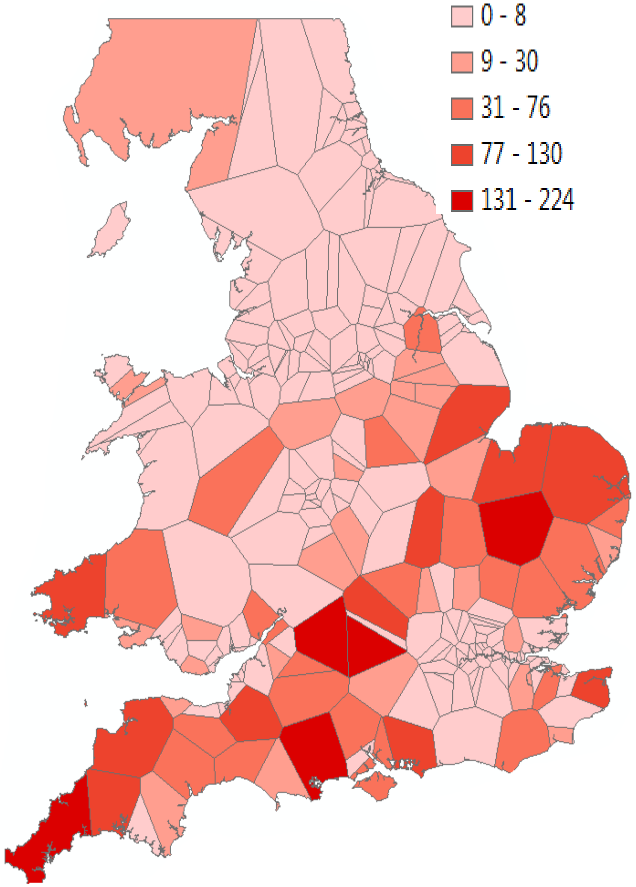
Koubli, E., Palmer, D., Rowley, P., & Gottschalg, R. (2016). Inference of missing data in photovoltaic monitoring datasets”. IET Renewable Power Generation. (2016).

Network Impacts: PV Output Maps for UK Solar Farms

Performance Per DNO
Modelled Output 2014 MWh





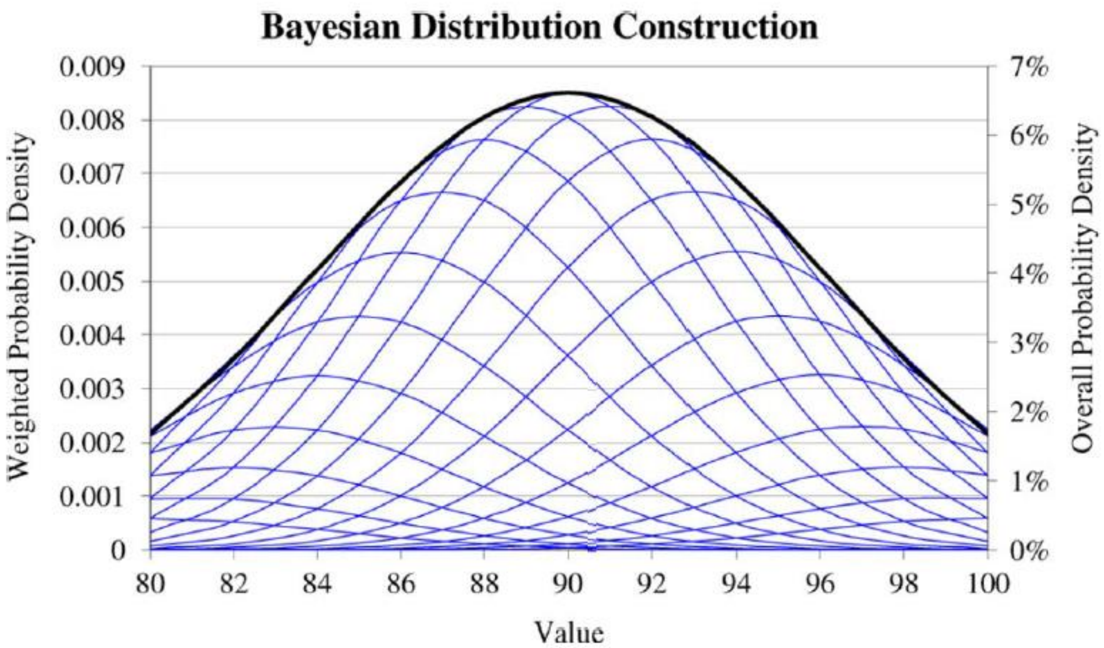


Solar farm output allocated to substation 2014 MW

Analysis under Uncertainty: Bayesian Methods

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

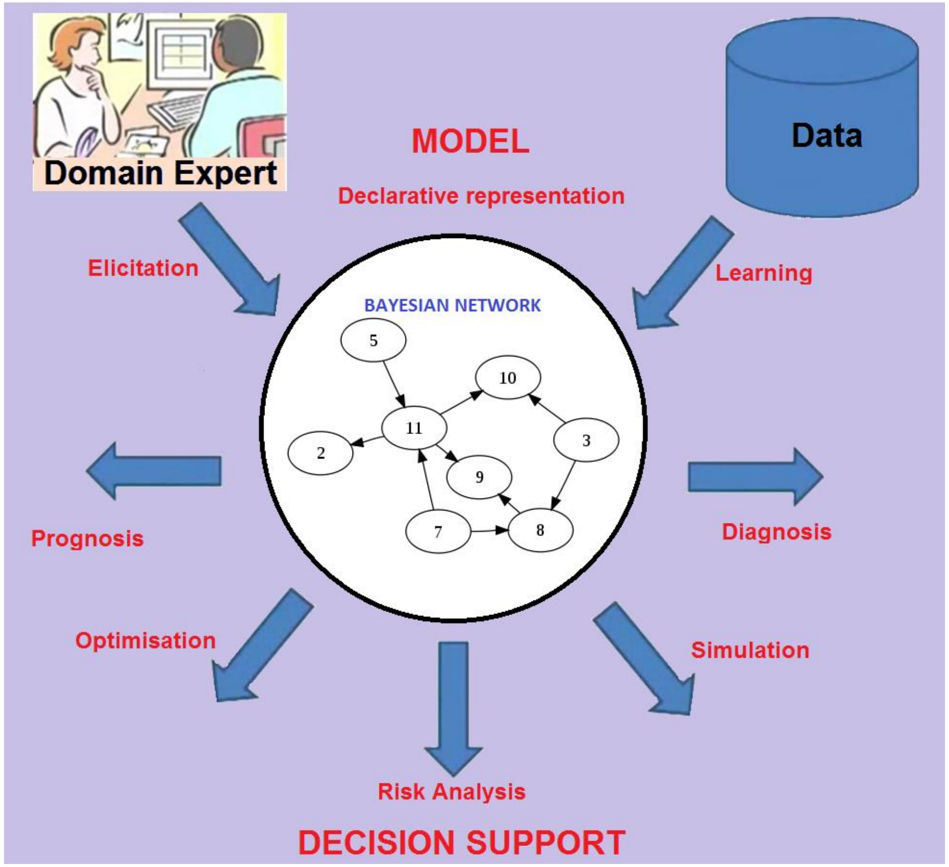
Bayes Rule: given a variable *A*, calculates the posterior distribution, $P(A|B)$ given evidence *B*, from the prior distributions, $P(A)$ and $P(B)$ and the likelihood $P(B|A)$



Wilson, Daniel M., Paul N. Rowley, and Simon J. Watson. "Utilizing a risk-based systems approach in the due diligence process for renewable energy generation." Systems Journal, IEEE 5.2 (2011): 223-232.

Bayesian Network Modelling

- A BN comprises a directed acyclic graph (DAG) and conditional probability tables (CPTs)
- A BN factorises a multi-dimensional (i.e. multi-parametric) joint probability distribution for a complex problem domain.
- Using probabilistic algorithms, evidence applied to input or output variables can deliver new posterior distributions to enable prognostic or diagnostic inference.



Bayesian Network Modelling

Key challenges are:

- To gather enough quantitative data to populate a BN with CPTs
- To determine the causal relationships between parameters (nodes)
- To accommodate different temporal scales.

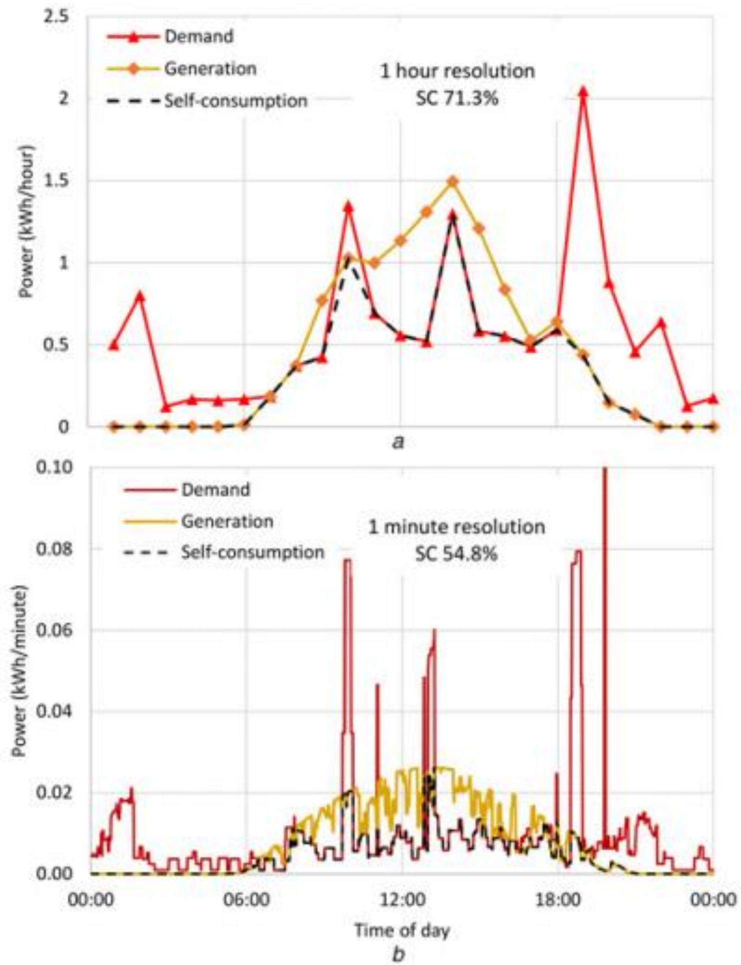


Fig. 1 *Sample simulated domestic electricity demand and PV generation profiles at*
a 1 min Resolution
b Same data aggregated to 1 h resolution

Leicester, P.A., Rowley, P.N. and Goodier, C.I., (2016). Probabilistic analysis of solar photovoltaic self-consumption using Bayesian network models. *IET Renewable Power Generation*, 10(4), pp.448-455. DOI: [10.1049/iet-rpg.2015.0360](https://doi.org/10.1049/iet-rpg.2015.0360).

PV Impact Analysis – Influence of Self Consumption

Here we have simulated 20,000 years of 1 minute time-step consumption and generation data to create an annualised probabilistic relationship between self-consumption predicted by annual solar PV yield and annual demand.

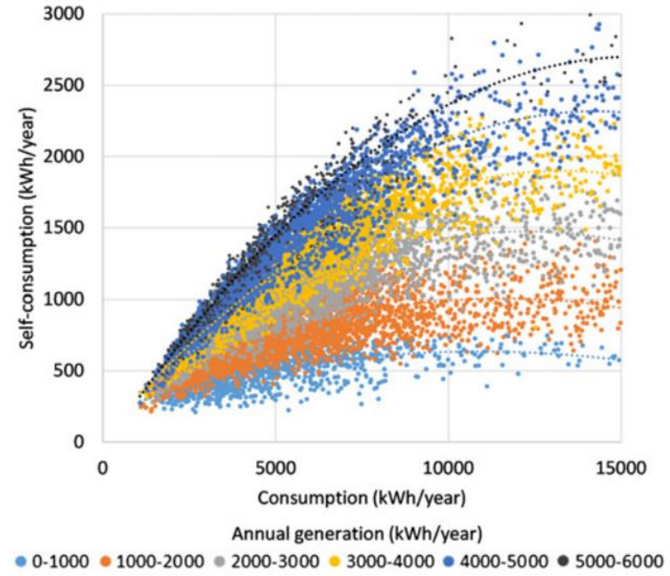


Fig. 4 *Annual PV SC as a function of annual electricity consumption segmented by annual system yield*

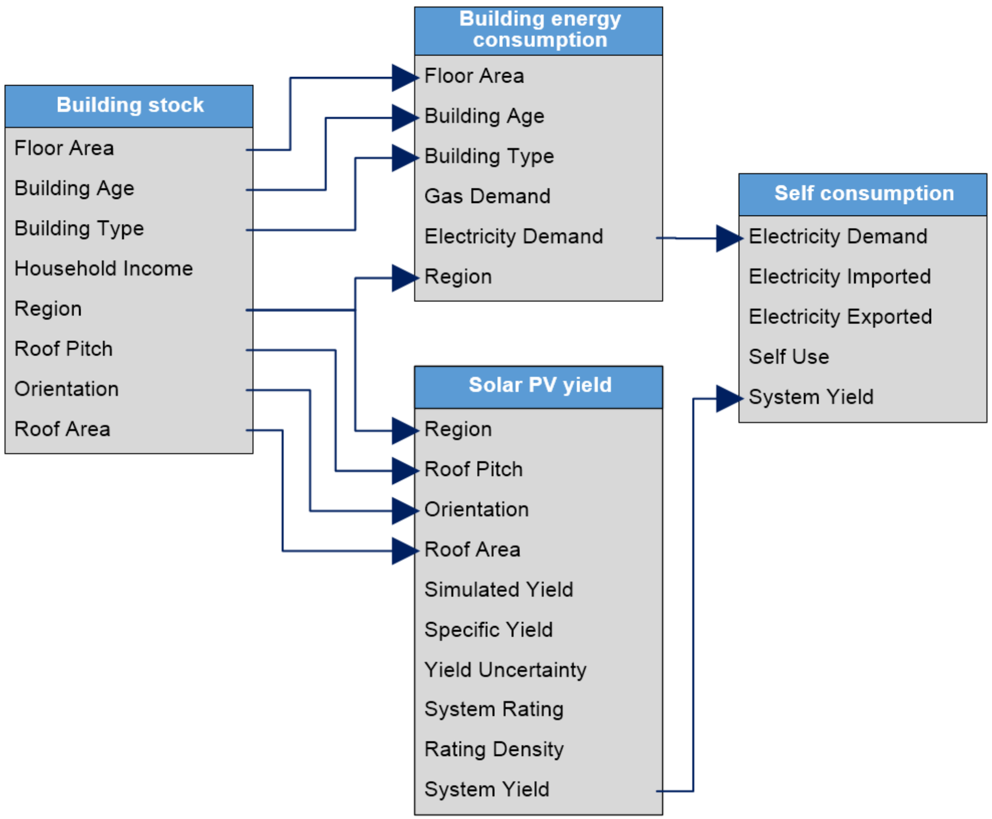
Table 2 Typical appliance load profiles for average domestic household related to occupancy archetypes with the average simulated SC observed

Occupancy archetype	Average SC, %
unoccupied 9:00–13:00	44
unoccupied 9:00–16:00	25
unoccupied 9:00–18:00	19
unoccupied 13:00–18:00	47
all-day occupied	69
all-day unoccupied	15

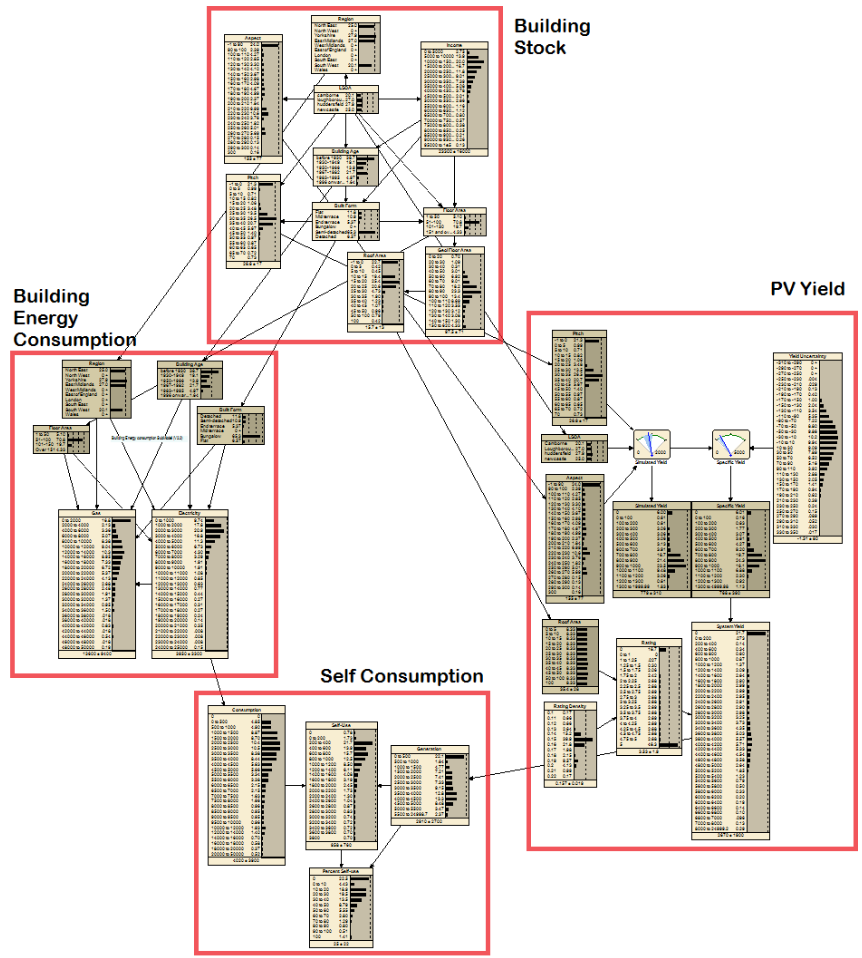
Leicester, Philip A., Chris I. Goodier, and Paul N. Rowley. "Probabilistic analysis of solar photovoltaic self-consumption using Bayesian network models." *IET Renewable Power Generation* 10.4 (2016): 448-455.

Bayesian Network Modelling

An autonomous BN model describes building stock, PV Yield, Building Energy Consumption and Self Consumption, and combined these into a larger 'OOBN'

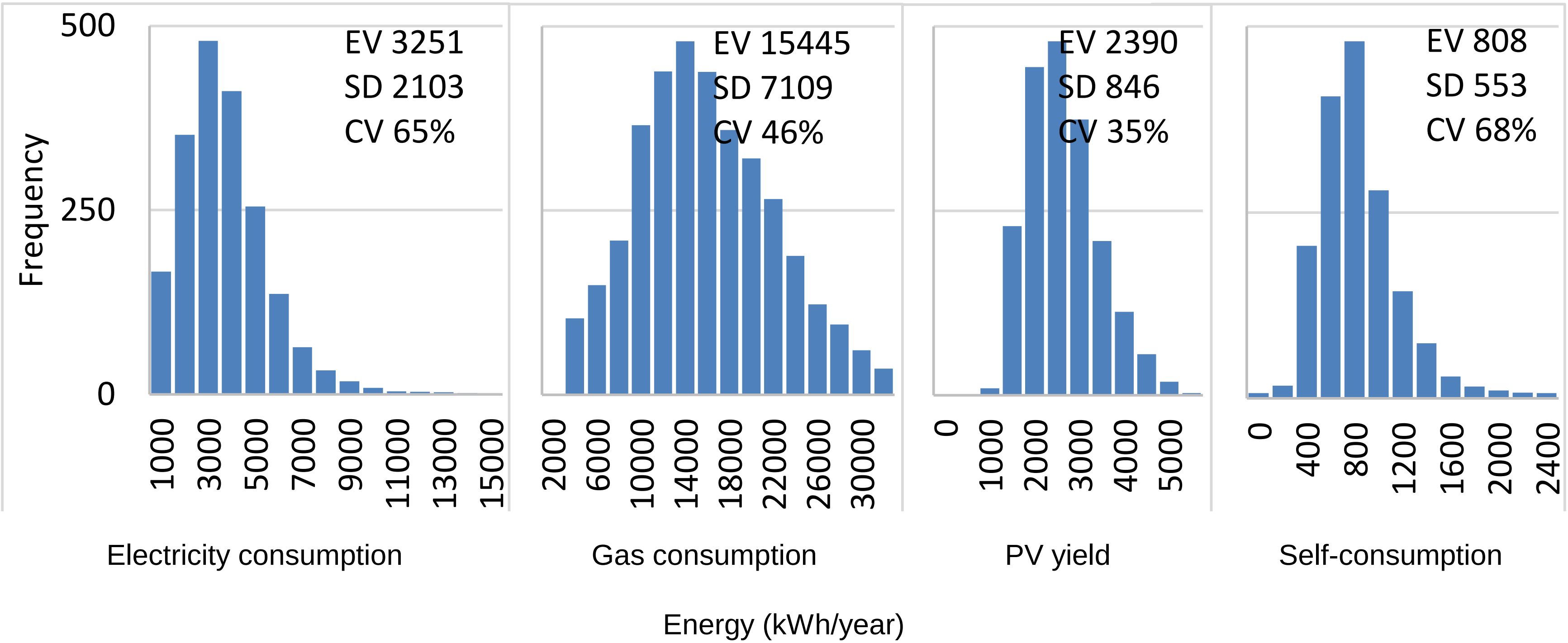


Entity Relationship Diagram View



OOBN Model in BN Software

Bayesian Network Modelling



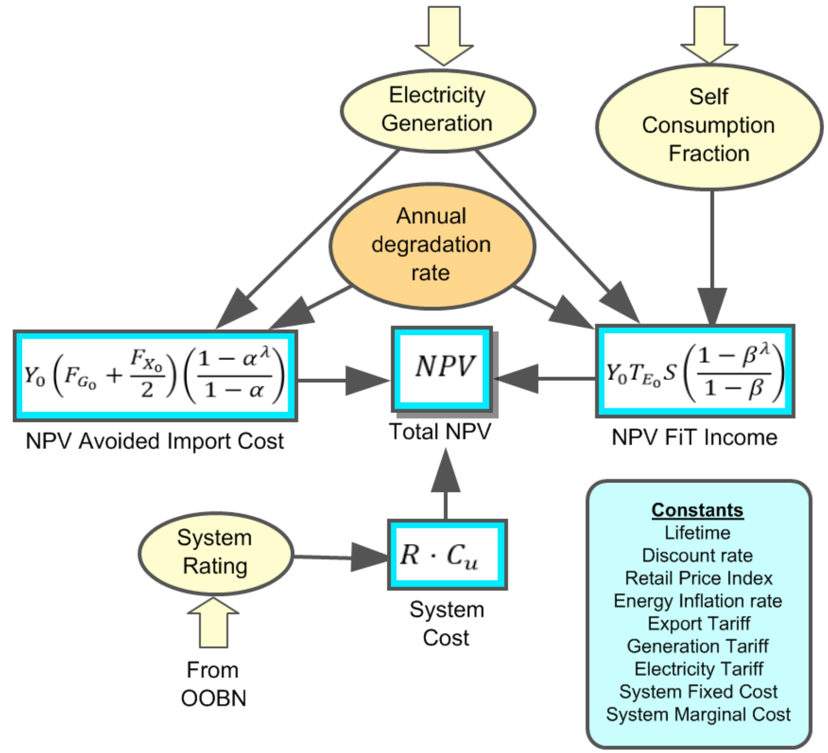
Resulting posterior distributions for a census area of Newcastle, England.

Techno-economics of Domestic-scale PV

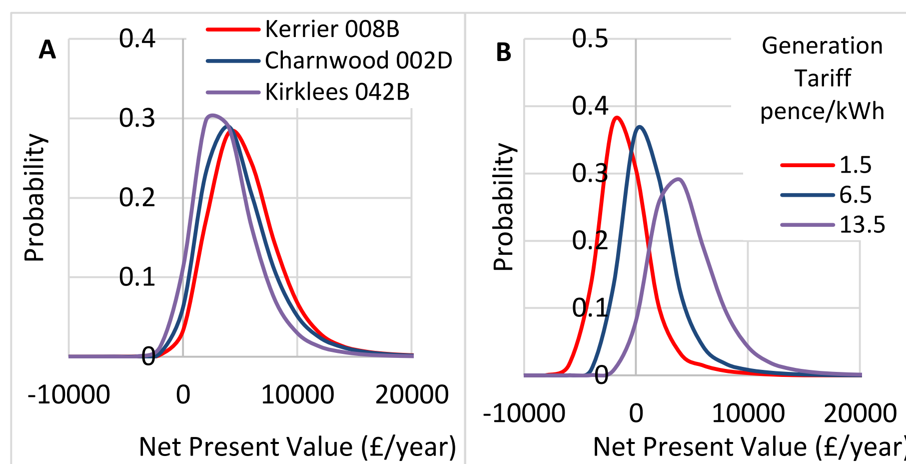
- Integration of probabilistic model outputs into a discounted cash flow BN model to calculate NPV

- PDFs allows a measure of risk to be determined.

- By defining some of the input parameters we can test the impact of different building orientations, geography and test policy scenarios (e.g. whether hurdle rates are realistically achieved with specific FiT rates)

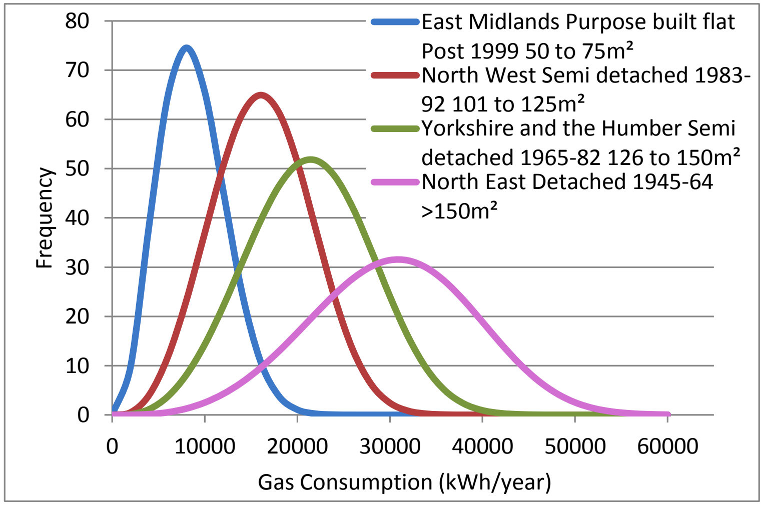


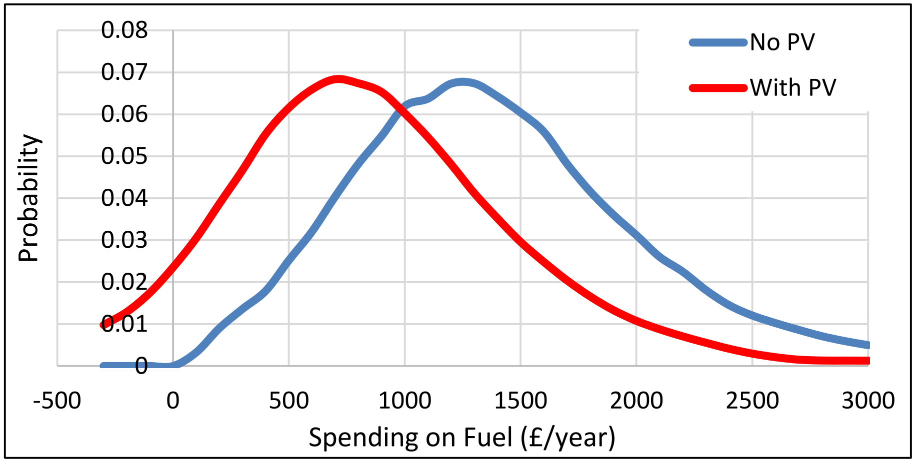
Leicester, P.A., Goodier, C.I. and Rowley, P.N. (2016). Probabilistic evaluation of solar photovoltaic systems using Bayesian networks: a discounted cash flow assessment. Prog. Photovolt: Res. Appl. DOI: [10.1002/pip.2754](https://doi.org/10.1002/pip.2754).



Socio-economics – fuel affordability

- UK has a detailed dataset of 4M records of domestic gas and electricity consumption.
- Also have good census data to allow iterative proportional fitting to estimate household income distributions.
- So we can estimate the impact of a low-carbon intervention, such as PV on household fuel bills.





Leicester P.A. (2015). The Development Of Object Oriented Bayesian Networks To Evaluate The Social, Economic And Environmental Impacts Of Solar PV. PhD Thesis, Loughborough University, England.

Domestic PV Business & Ownershio Models

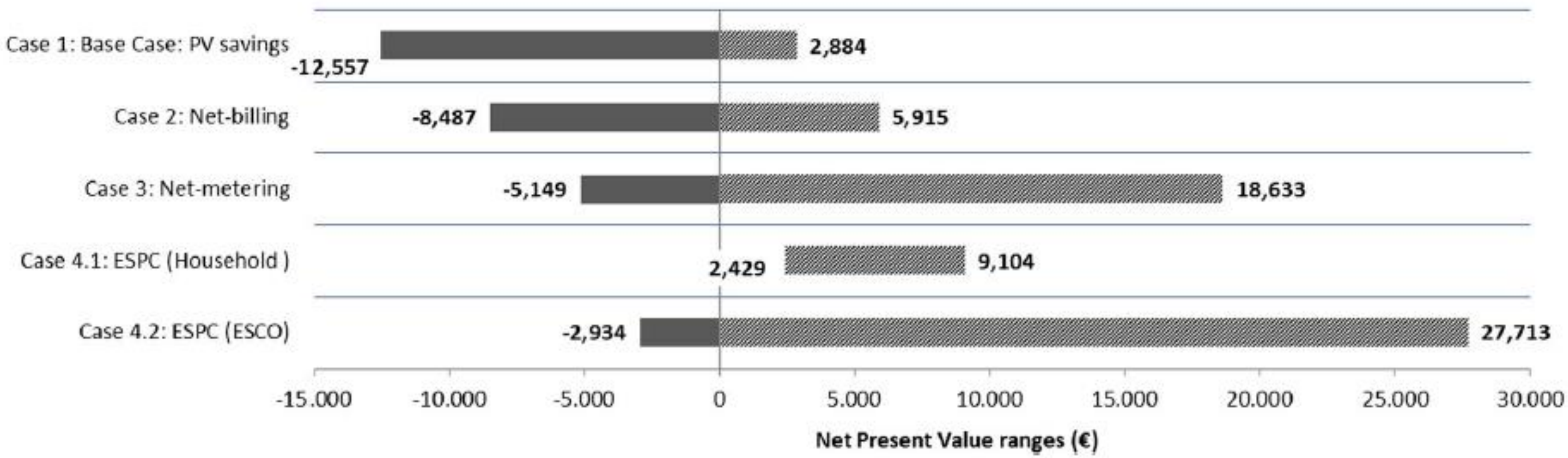


Figure 12. Ranges[5] for NPV after MC simulation for each of the business models.

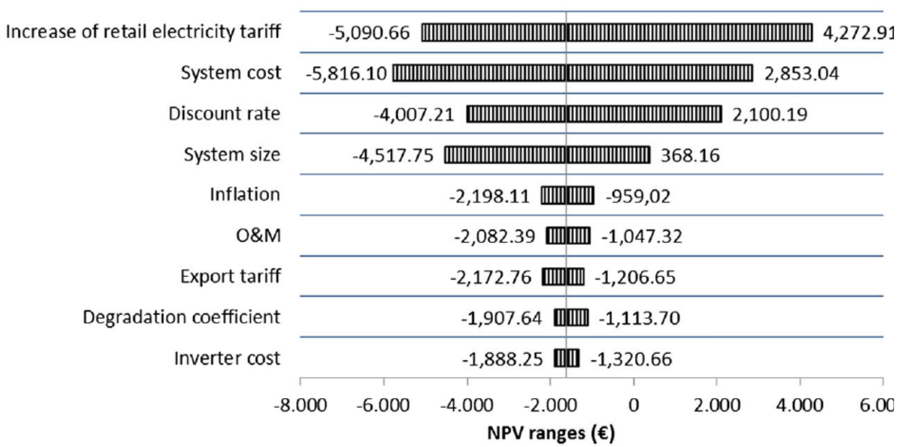


Figure 11. Sensitivity analysis for NPV for Case 3: Net-billing.

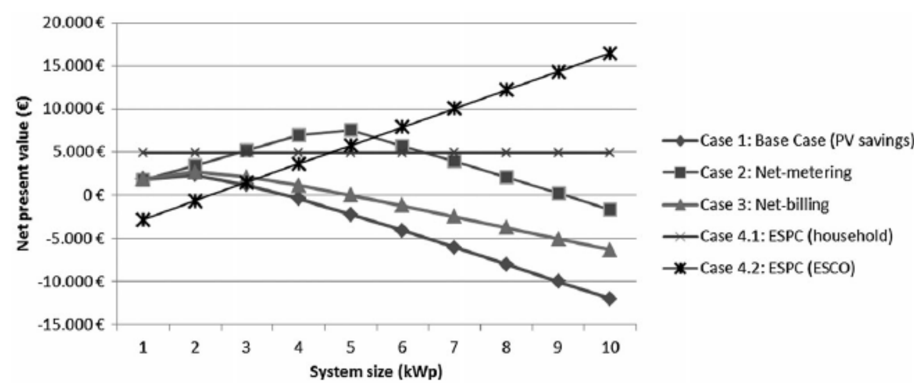
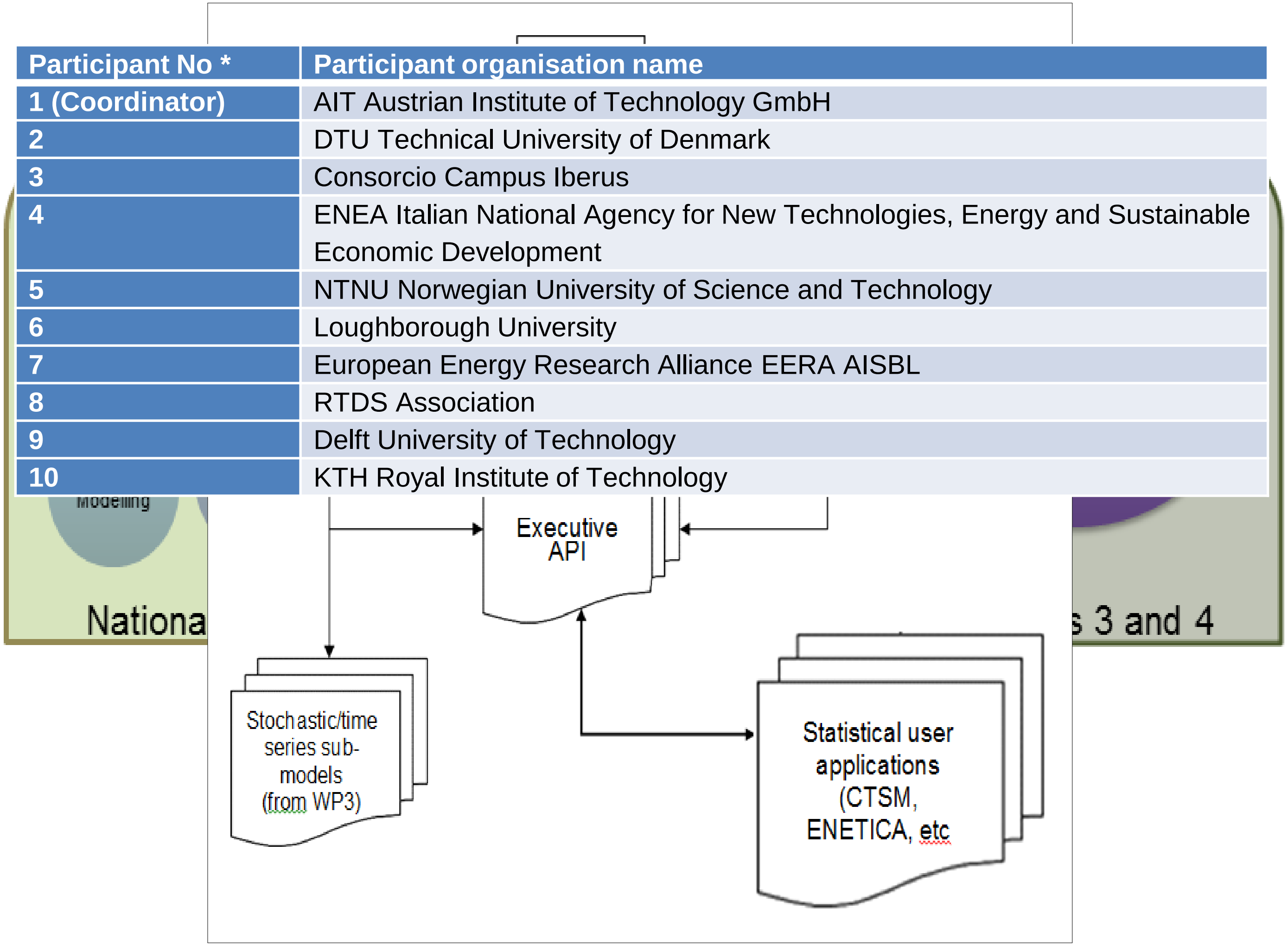


Figure 13. Sensitivity analysis for NPV according to system size variation for all cases.

Betz, S., Caneva, S., Weiss, I., & Rowley, P. (2016). Photovoltaic energy competitiveness and risk assessment for the South African residential sector. Progress in Photovoltaics: Research and Applications.(2016).

New Research – EERA Get2Z

Participant No *	Participant organisation name
1 (Coordinator)	AIT Austrian Institute of Technology GmbH
2	DTU Technical University of Denmark
3	Consorcio Campus Iberus
4	ENEA Italian National Agency for New Technologies, Energy and Sustainable Economic Development
5	NTNU Norwegian University of Science and Technology
6	Loughborough University
7	European Energy Research Alliance EERA AISBL
8	RTDS Association
9	Delft University of Technology
10	KTH Royal Institute of Technology



Summary

- Holistic approaches can illuminate social, technical, economic, political and environmental aspects.
- Adaptive data-driven modelling can yield new insights not easily obtainable by other means
- Can be utilised to create robust decision support and policy tools for key stakeholders.
- Thank you!