WE NEED TO TALK ABOUT LOW VOLTAGE

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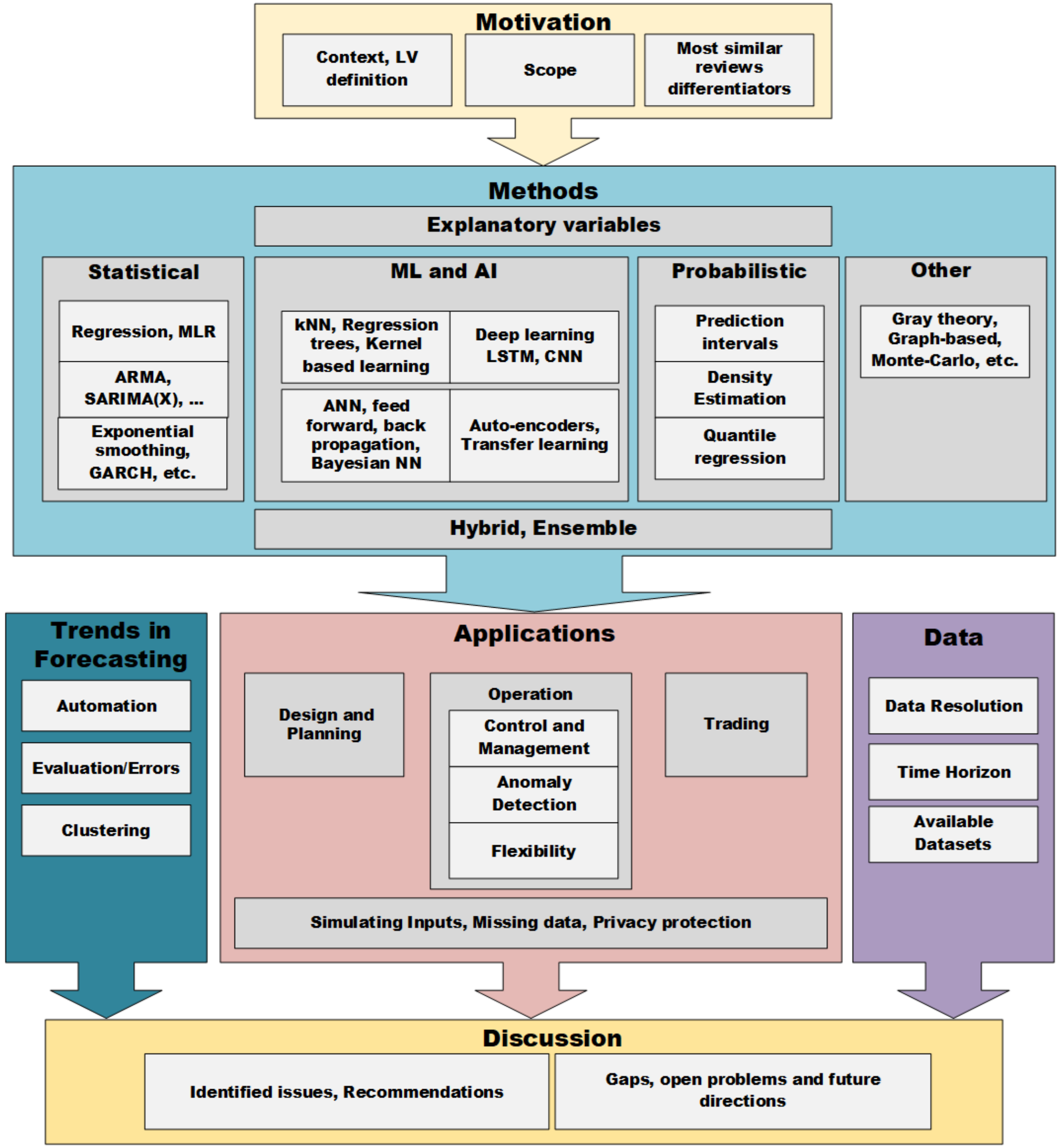
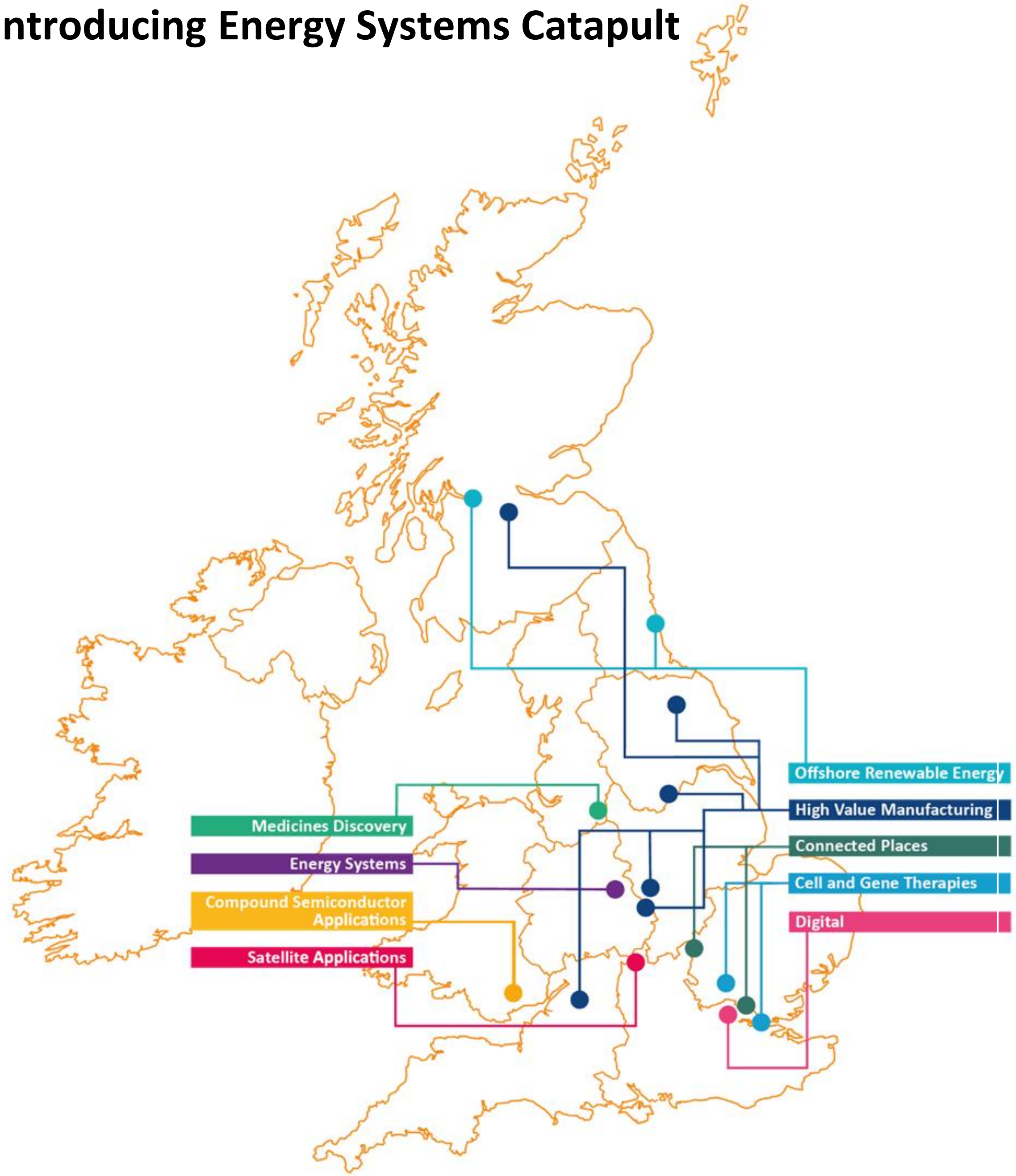
CONTENT

- Context and Motivation
- Features and observations in LV systems
- Research Challenges
  - Methodological problems
  - Data
- Trends & Gaps
- Recommendations



Introducing Energy Systems Catapult



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9 catapults

Technical capabilities, equipment, and other resources

Solve key problems and develop new products and services

Bridge the gap between stakeholders in the sector

Open up opportunities for innovators, in the UK and globally

Energy Data Taskforce

- In October 2018 the Energy Data Taskforce was established to provide Government, Ofgem and Industry with a set of recommendations on how data can assist with unlocking the opportunities provided by a modern, decarbonised and decentralised Energy System at the best value to consumers.

- In June 2019 the Energy Data Taskforce published a report entitled

  A Strategy for a Modern Digitalised Energy System

  which presents five key recommendations that will modernise the UK energy system and drive it towards a net zero carbon future through an integrated data and digital strategy throughout the sector.

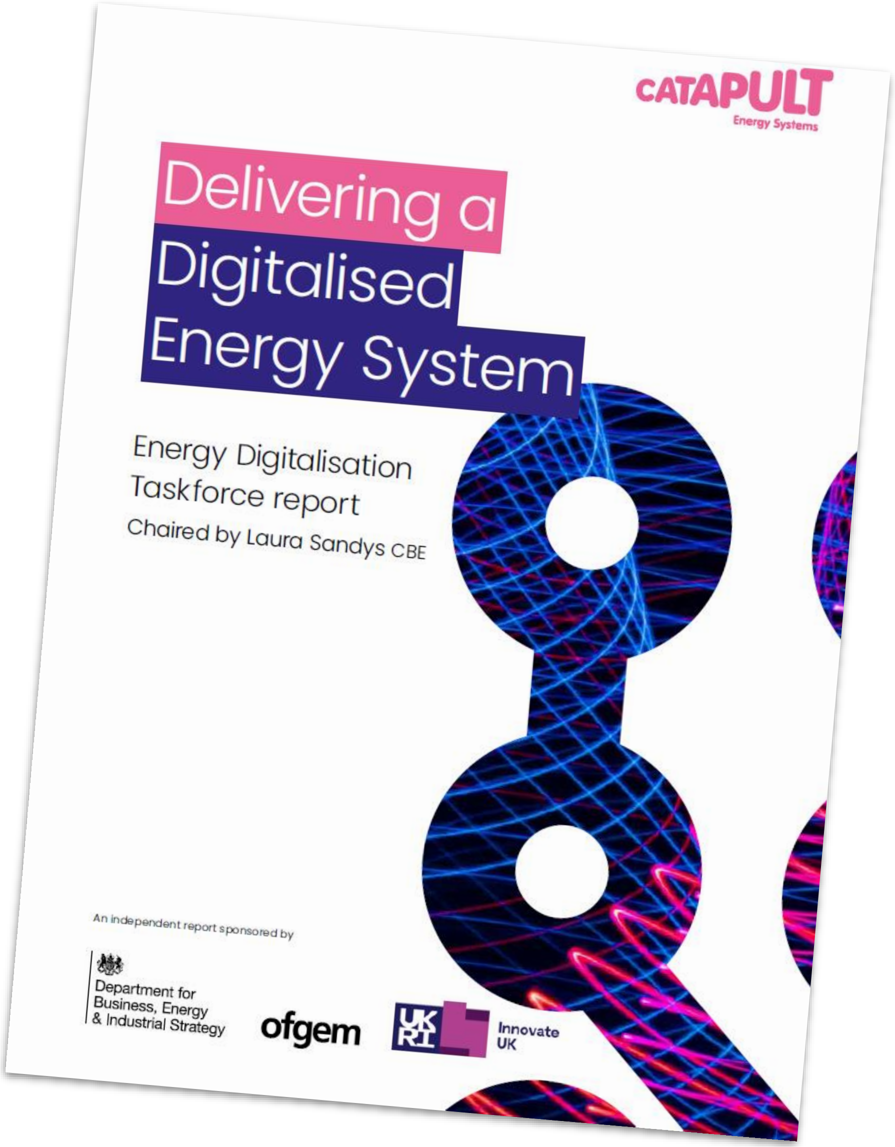
Commissioned by:

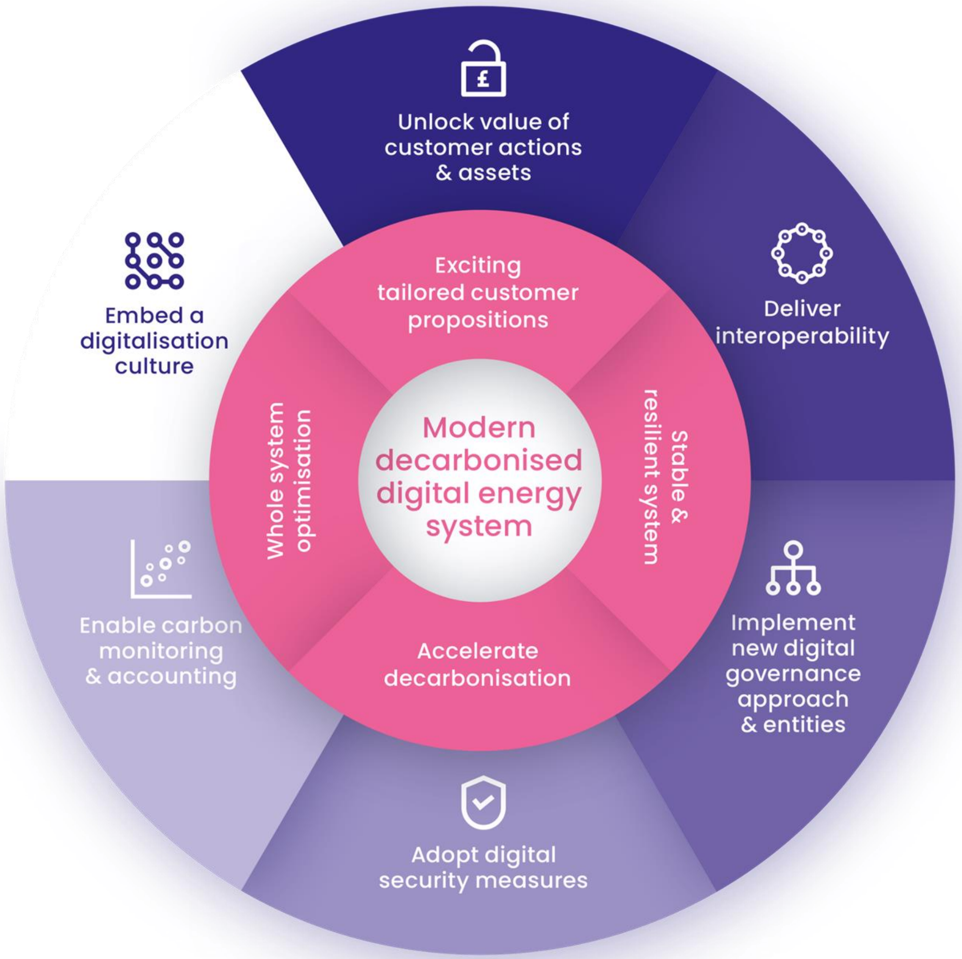
ofgem Making a positive difference for energy consumers

Innovate UK

Department for Business, Energy & Industrial Strategy

Energy Digitalisation Taskforce

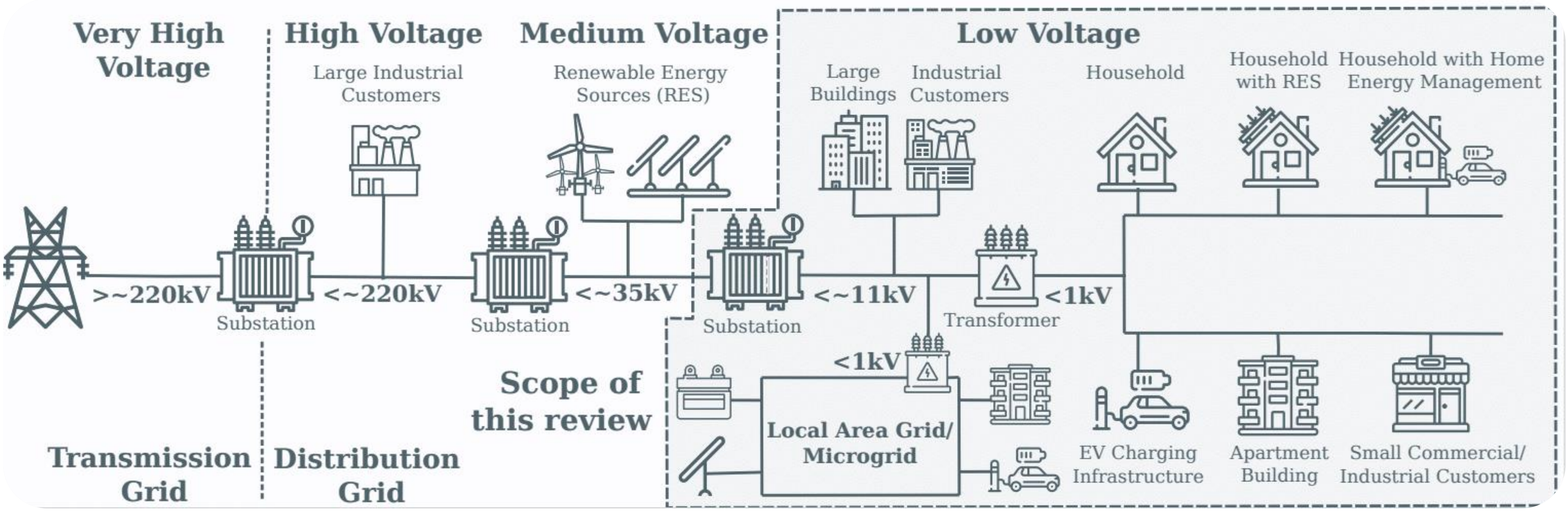




https://es.catapult.org.uk/report/delivering-a-digitalised-energy-system/

Context: LV Networks

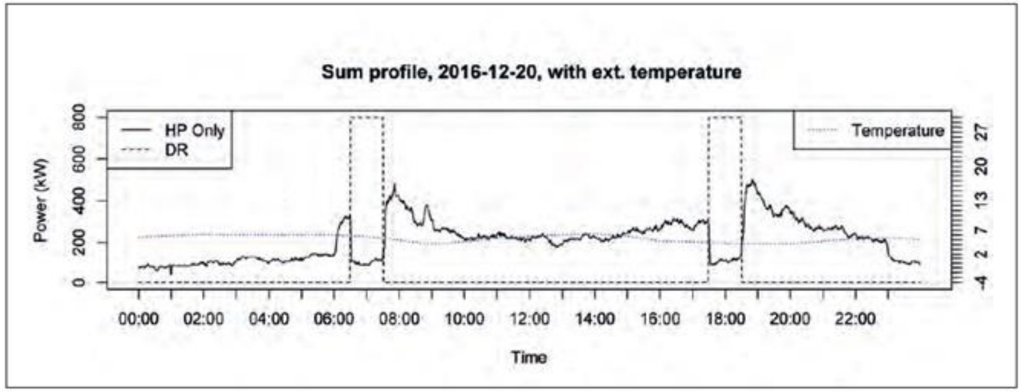
- What do we mean by Low Voltage?



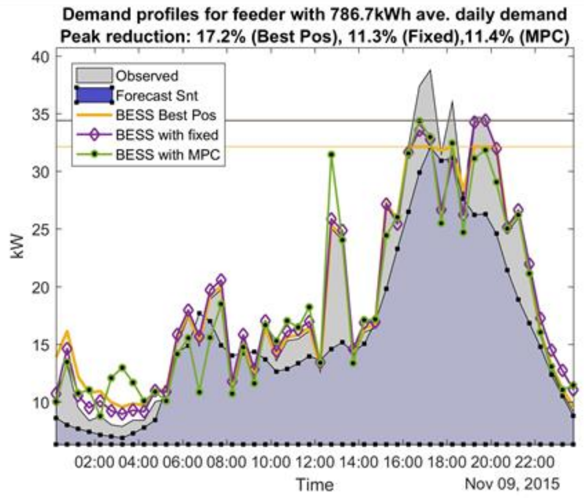
Picture from Review of low voltage load forecasting: Methods, applications, and recommendations, Haben et al. Applied Energy, 2021. https://doi.org/10.1016/j.apenergy.2021.117798

LV Forecasting Applications

Heat pump demand side response

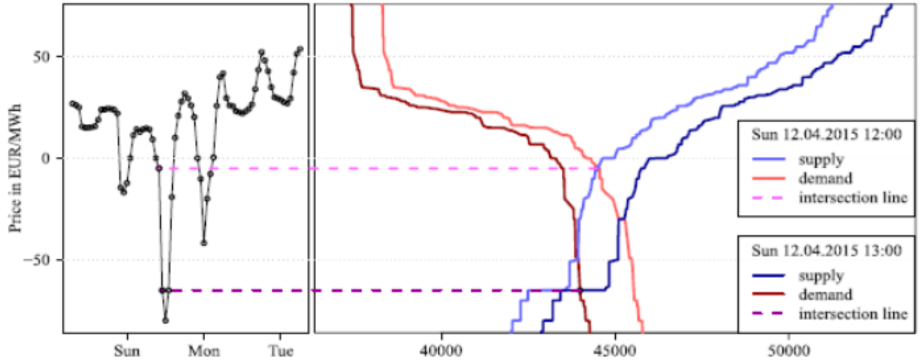


Smart management systems



Long term scenario planning

Day ahead wholesale electricity markets



- **Network Design and Planning** – location and sizing of substations, location sectionalising switches, storage location.
- **Network Operations and Control** – grid management, storage, feed-in limits, minimise curtailment losses, cost reductions, maximise PV hosting capacity, Voltage control …
- **Anomaly Detection –** theft detection systems, malicious attacks, early warning systems, …
- **Trading** – Peer-to-peer trading, feed in to market responses, energy trading algorithms, ….
- **Simulating Inputs, Missing data, Privacy Protection** - imputing missing values, generating pseudo observations for state-estimation, differential privacy, …

Pictures clockwise from top left:
http://media.ontheplatform.org.uk/sites/default/files/GMCA%20NEDO%20Smart%20Communities%20Exec%20Report%20FINAL.pdf
Evaluating the effectiveness of storage control in reducing peak demand on low-voltage feeders, T. Yunusov, S. Haben, T. Lee, F. Ziel, W. Holderbaum, B. Potter, Proceedings CIRED 2017
Long term individual load forecast under different electrical vehicles uptake scenarios, A. Poghosyan, D. V. Greetham, S. Haben and T. Lee, Applied Energy, vol. 157, pp. 699--709, 2015
Electricity price forecasting using sale and purchase curves: The X-Model, Florian Ziel, Rick Steinert, Energy Economics, Volume 59, 2016,

Motivating Example: Storage Control

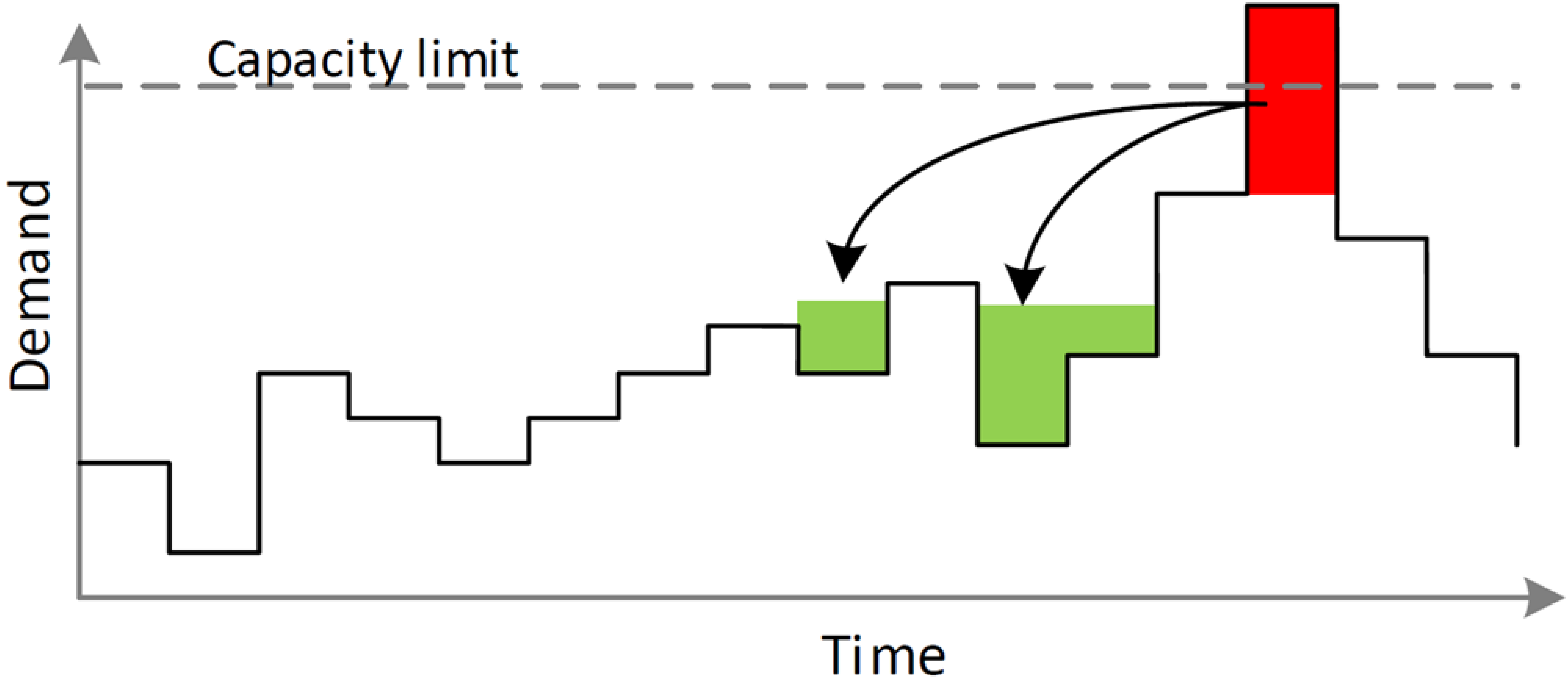


Photo courtesy Timur Yunusov

Thames Valley Vision Project

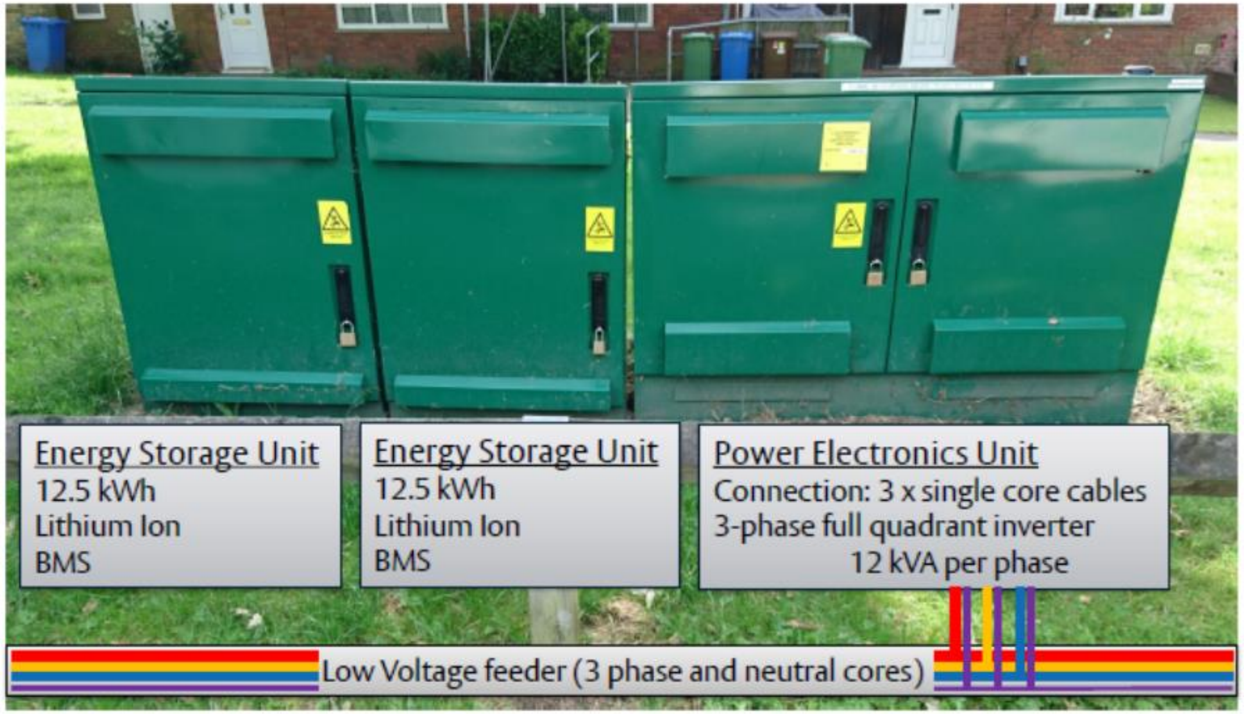
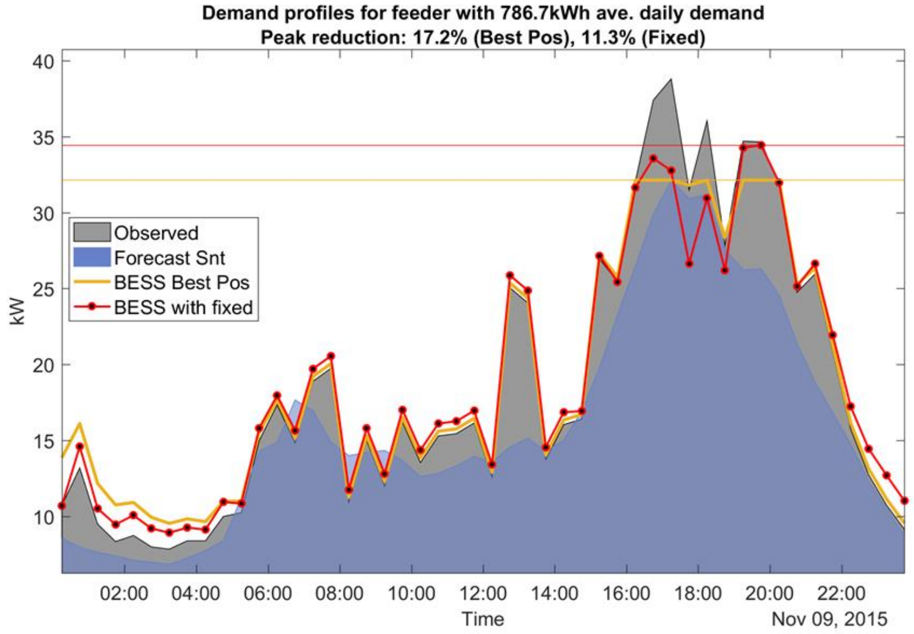
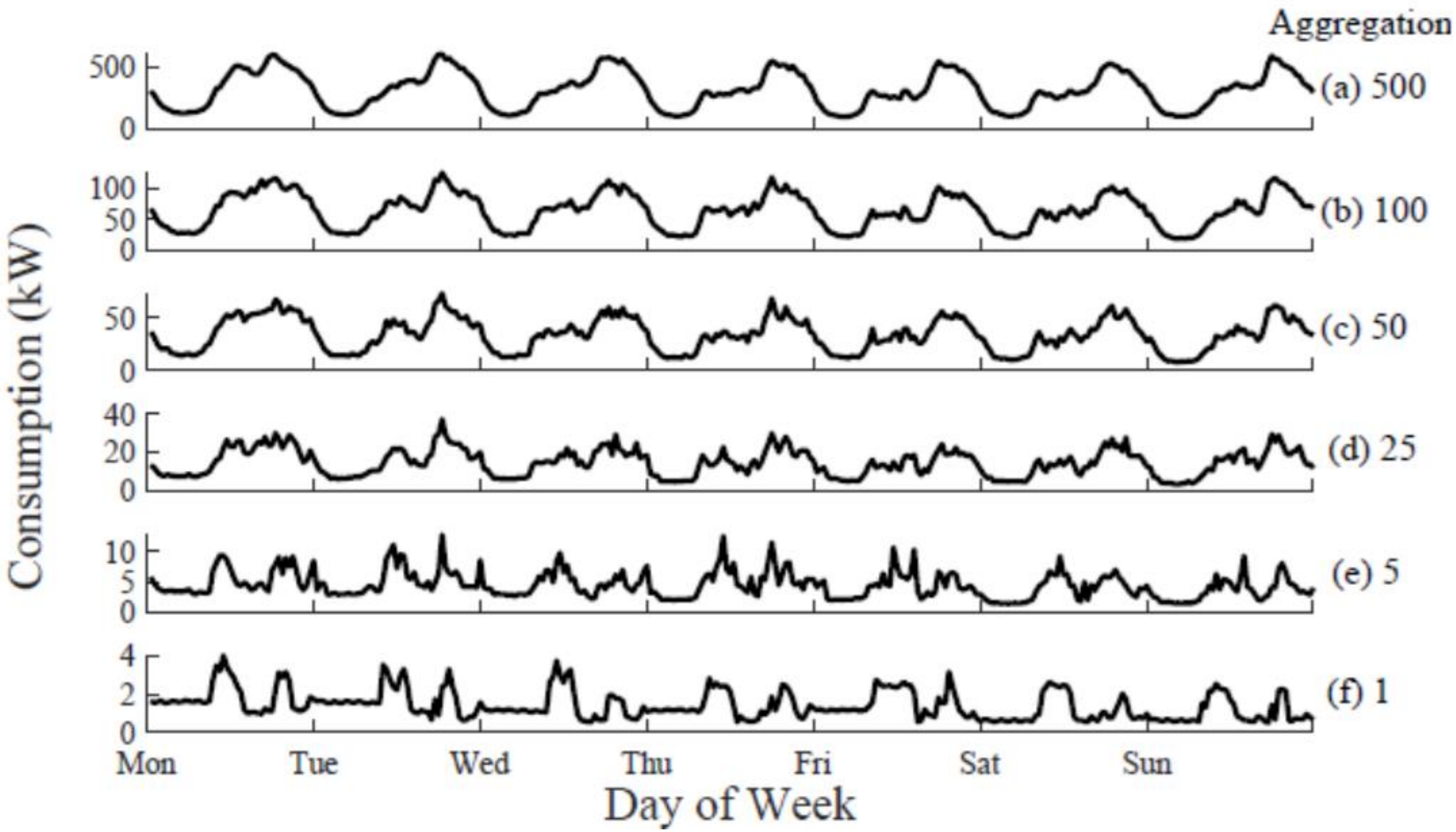


Photo courtesy Timur Yunusov



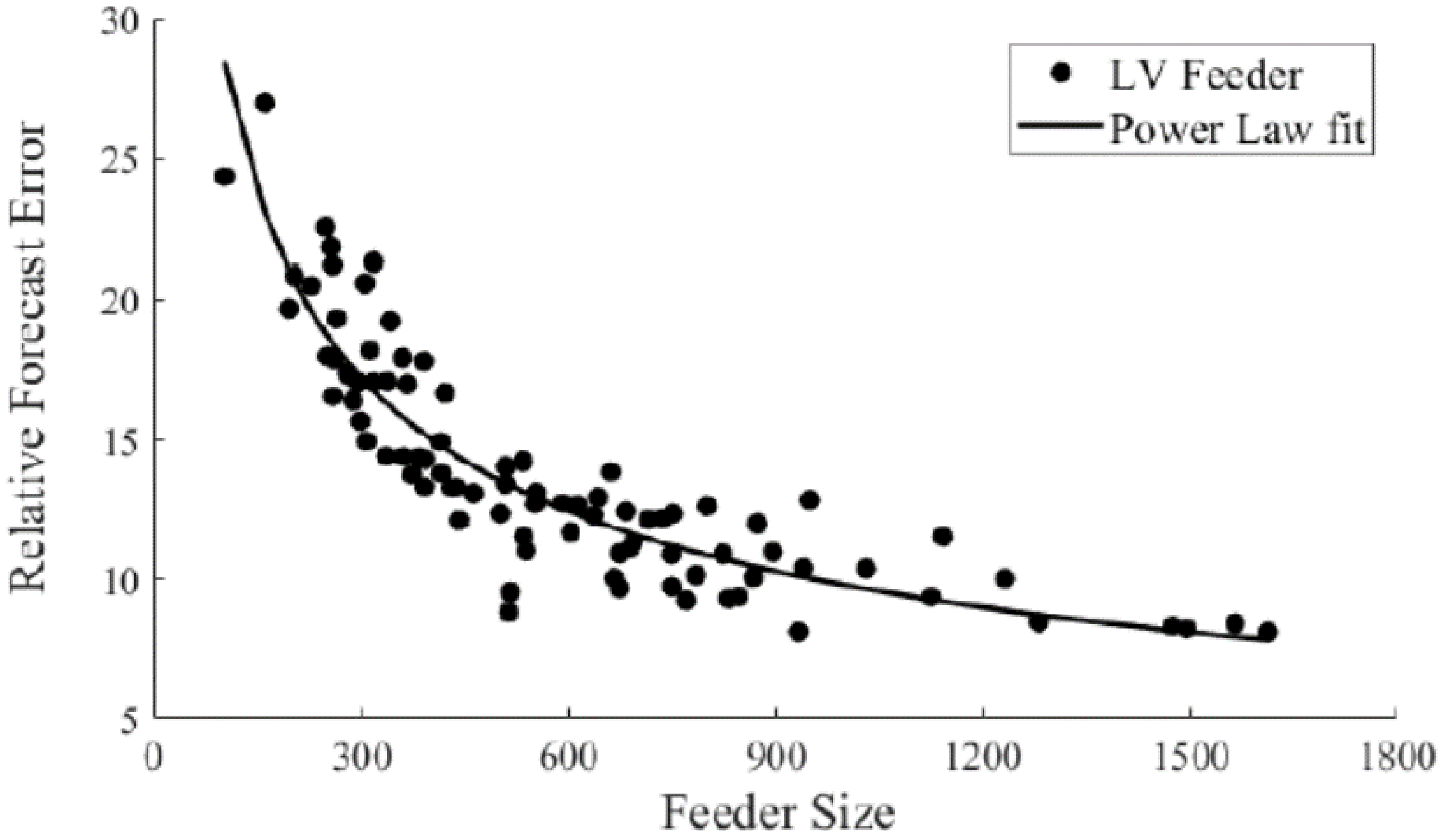
Picture: Evaluating the effectiveness of storage control in reducing peak demand on low-voltage feeders, T. Yunusov, S. Haben, T. Lee, F. Ziel, W. Holderbaum, B. Potter, Proceedings CIRED 2017

LV networks: Simply aggregations of smart meters?



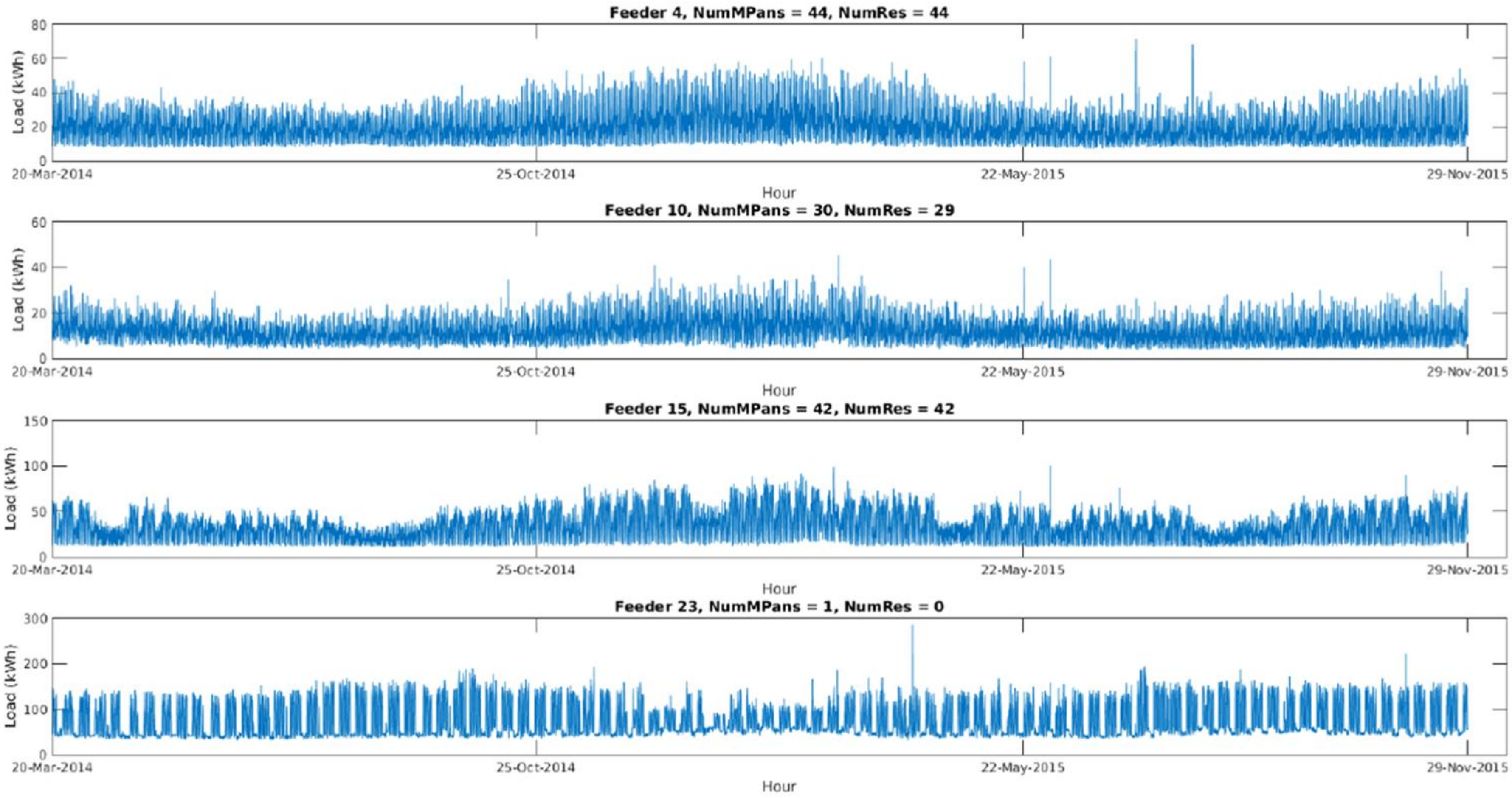
Pictures from Review of low voltage load forecasting: Methods, applications, and recommendations, Haben et al. Applied Energy, 2021. https://doi.org/10.1016/j.apenergy.2021.117798

Accuracy/Outputs with Aggregation

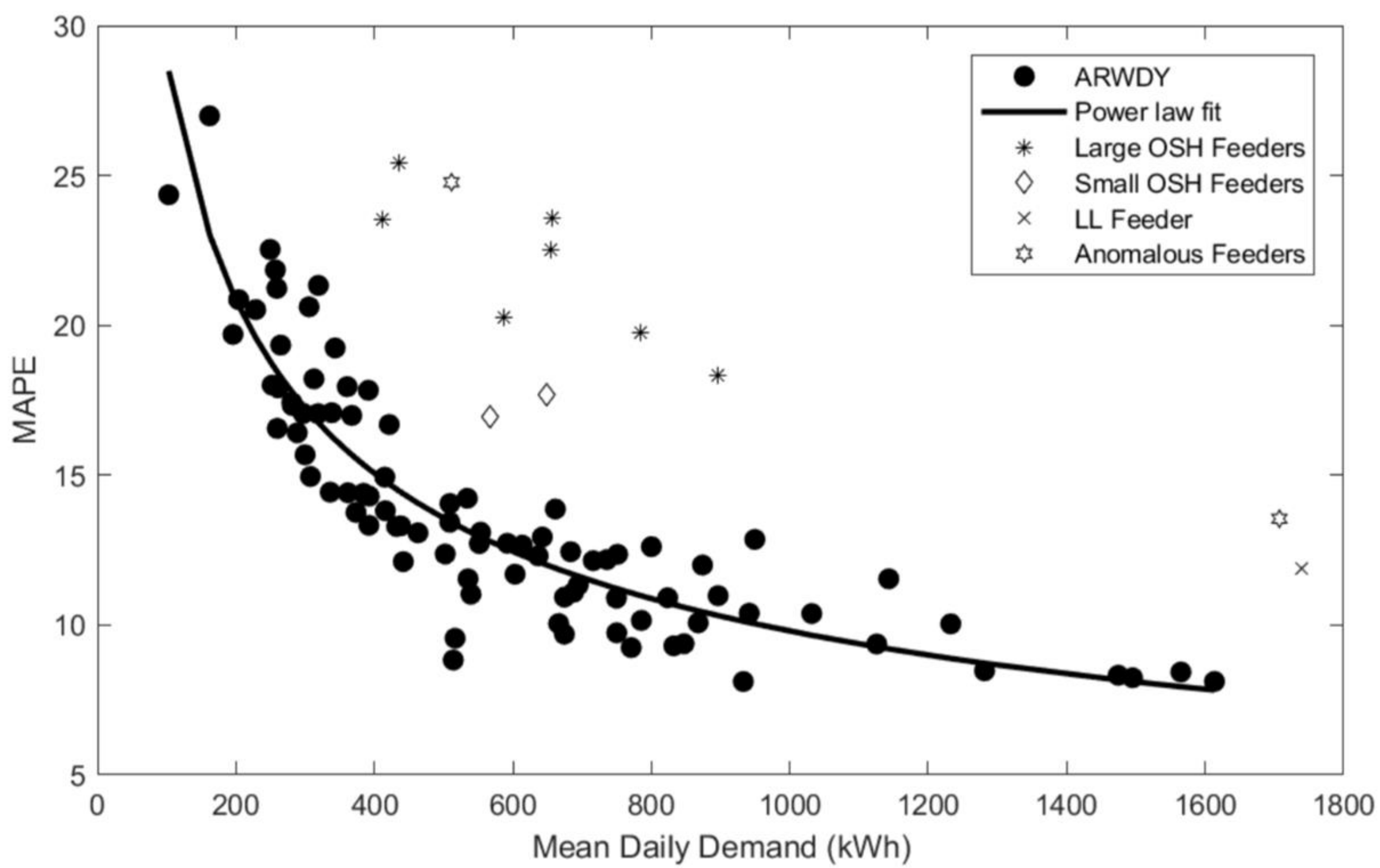


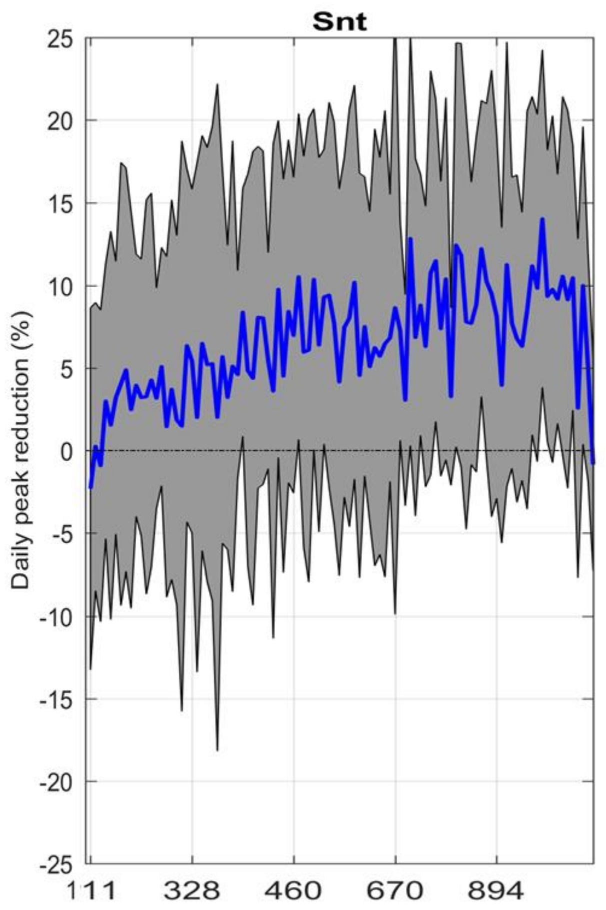
Pictures from Review of low voltage load forecasting: Methods, applications, and recommendations, Haben et al. Applied Energy, 2021. https://doi.org/10.1016/j.apenergy.2021.117798

LV Network Data



Aggregation vs. Accuracy: Less Straightforward

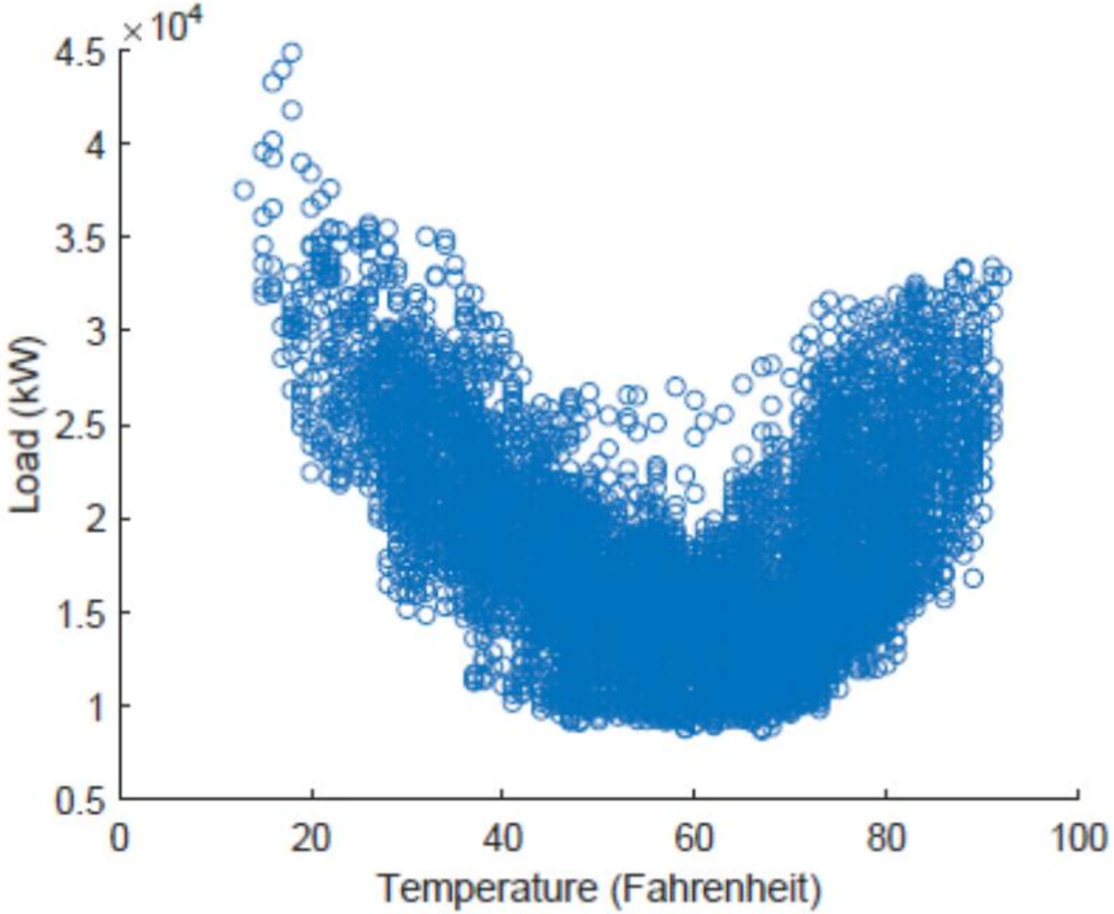




Sources: Short Term Load Forecasts of Low Voltage Demand and the Effects of Temperature, S. Haben, G. Giasemidis, F. Ziel and S. Arora, International Journal of Forecasting, 2019.
Evaluating the effectiveness of storage control in reducing peak demand on low voltage feeders, T Yunusov, S Haben, T Lee, F Ziel, W Holderbaum, B Potter, 24th International Conference & Exhibition on Electricity Distribution (CIRED), Glasgow, 2017.

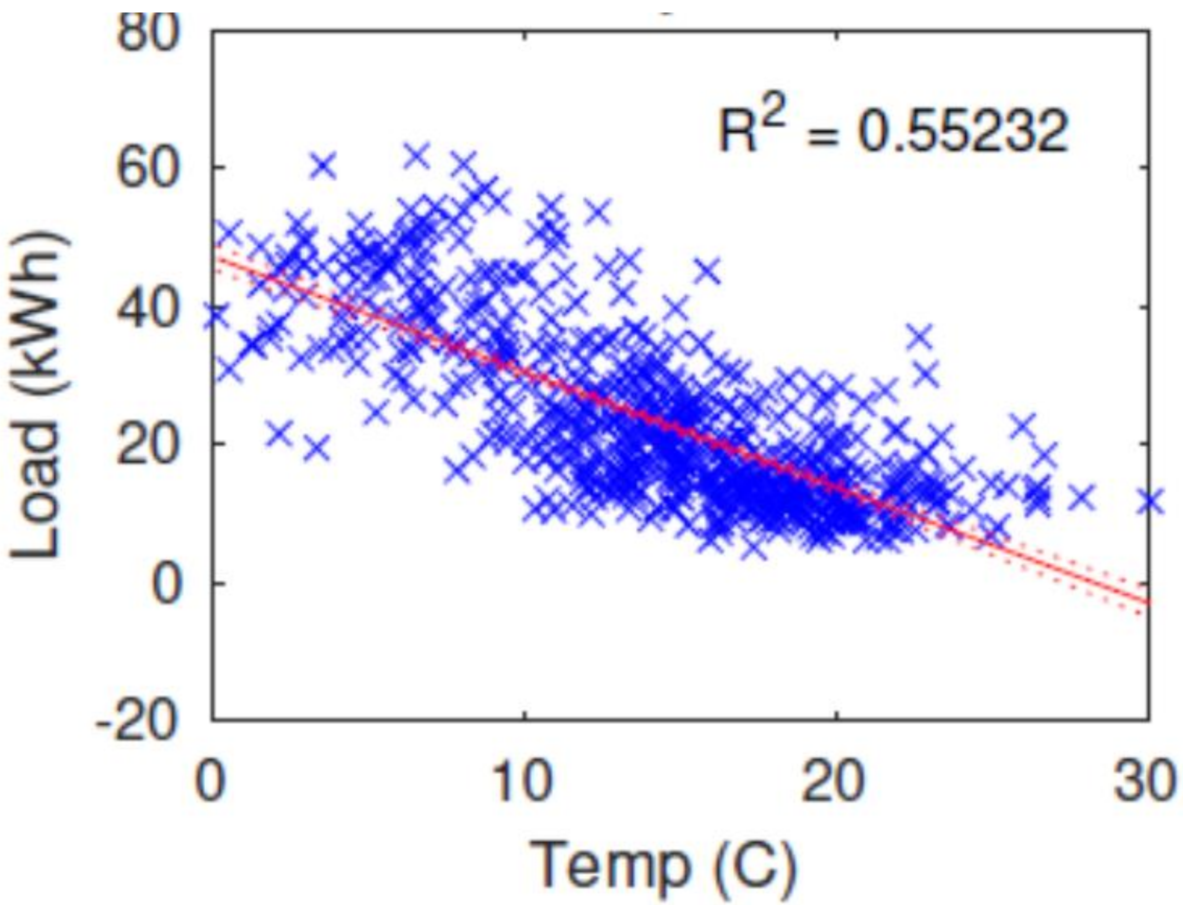
Weather Effects

GEFCOM 2014 – US Data

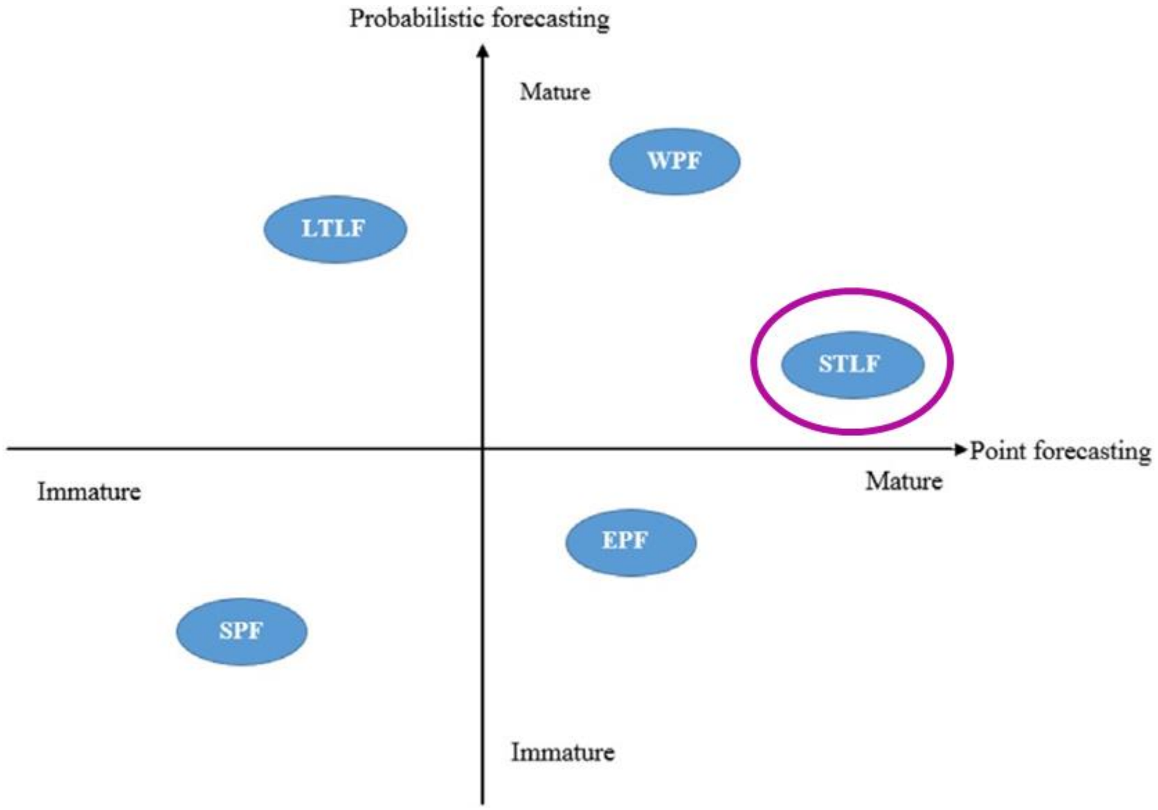


GEFCOM data from: Tao Hong, Pierre Pinson, Shu Fan, Hamidreza Zareipour, Alberto Troccoli and Rob J. Hyndman, "Probabilistic energy forecasting: Global Energy Forecasting Competition 2014 and beyond", International Journal of Forecasting, vol.32, no.3, pp 896-913, July-September, 2016.

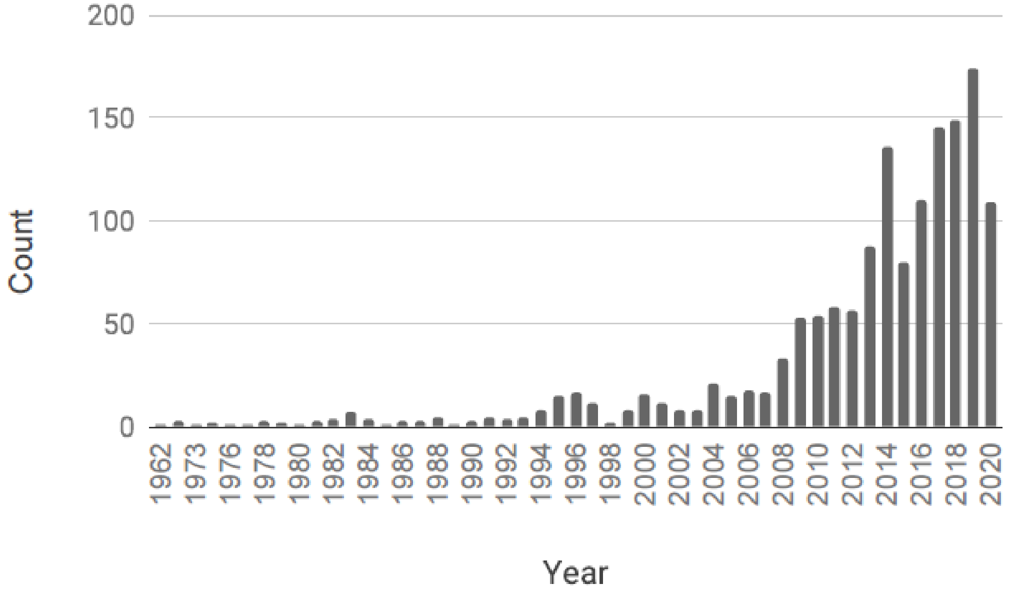
TVV Data 2016 – UK LV demand Data

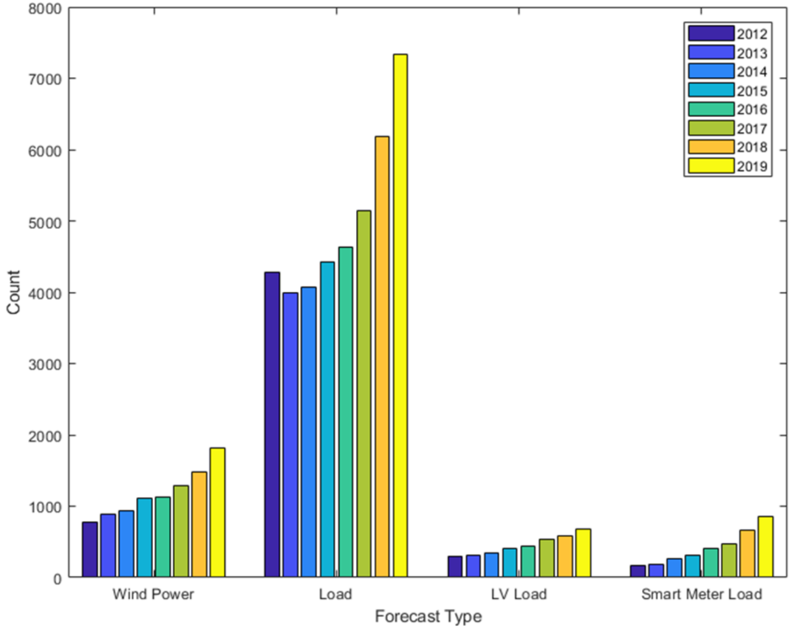


Current Status: LV forecasting



Picture credit: Probabilistic energy forecasting: Global Energy Forecasting Competition 2014 and beyond, T. Hong, P. Pinson, S. Fan, H. Zareipour, A. Troccoli, R. J. Hyndman, International Journal of Forecasting, 2016.

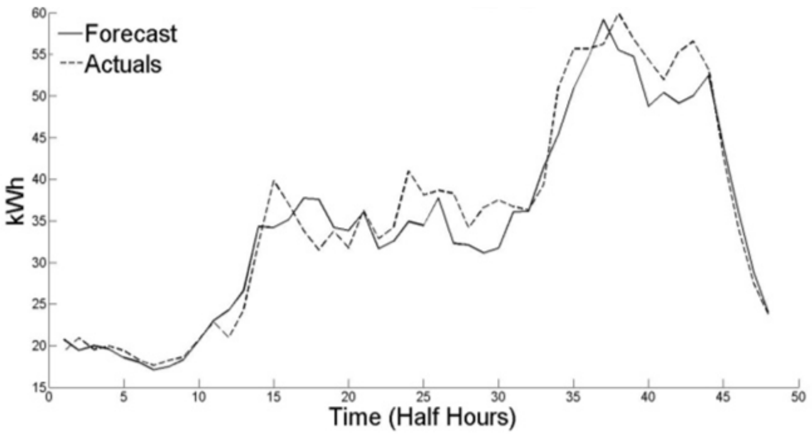




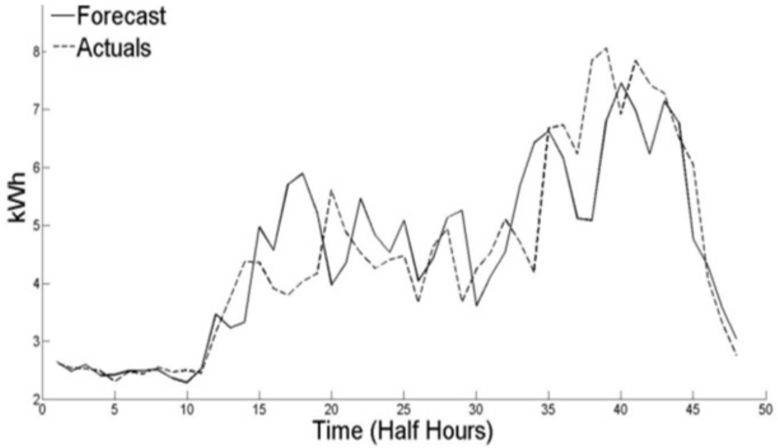
Source data: Google scholar.

Lower Aggregation Challenges

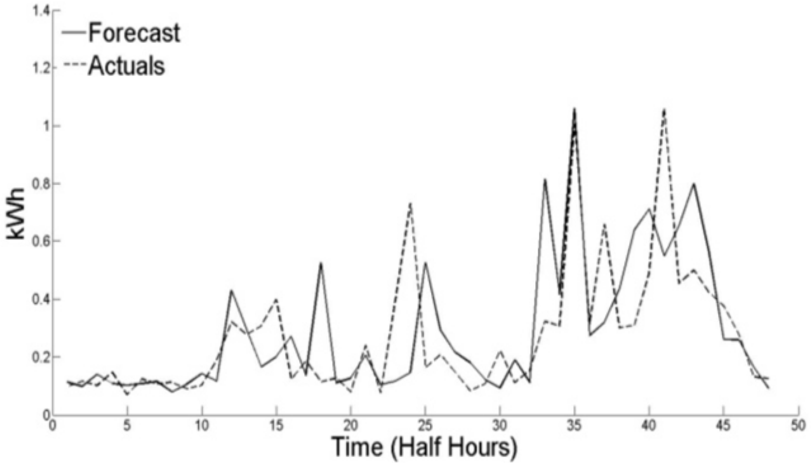
150 household



20 household

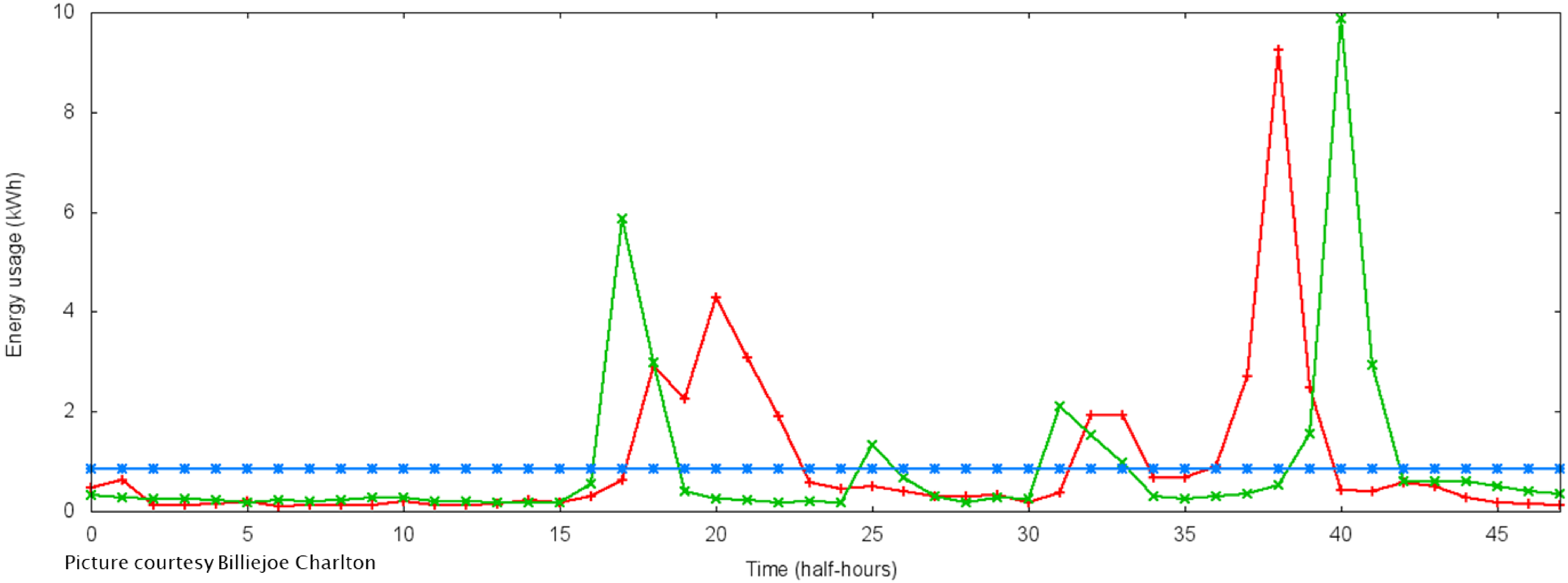


1 household



Double Penalty Effect: Flat forecast skill!

$$E_p = \|\mathbf{f} - \mathbf{x}\|_p = \left(\sum_{i=1}^{n} |f_i - x_i|^p \right)^{1/p}$$



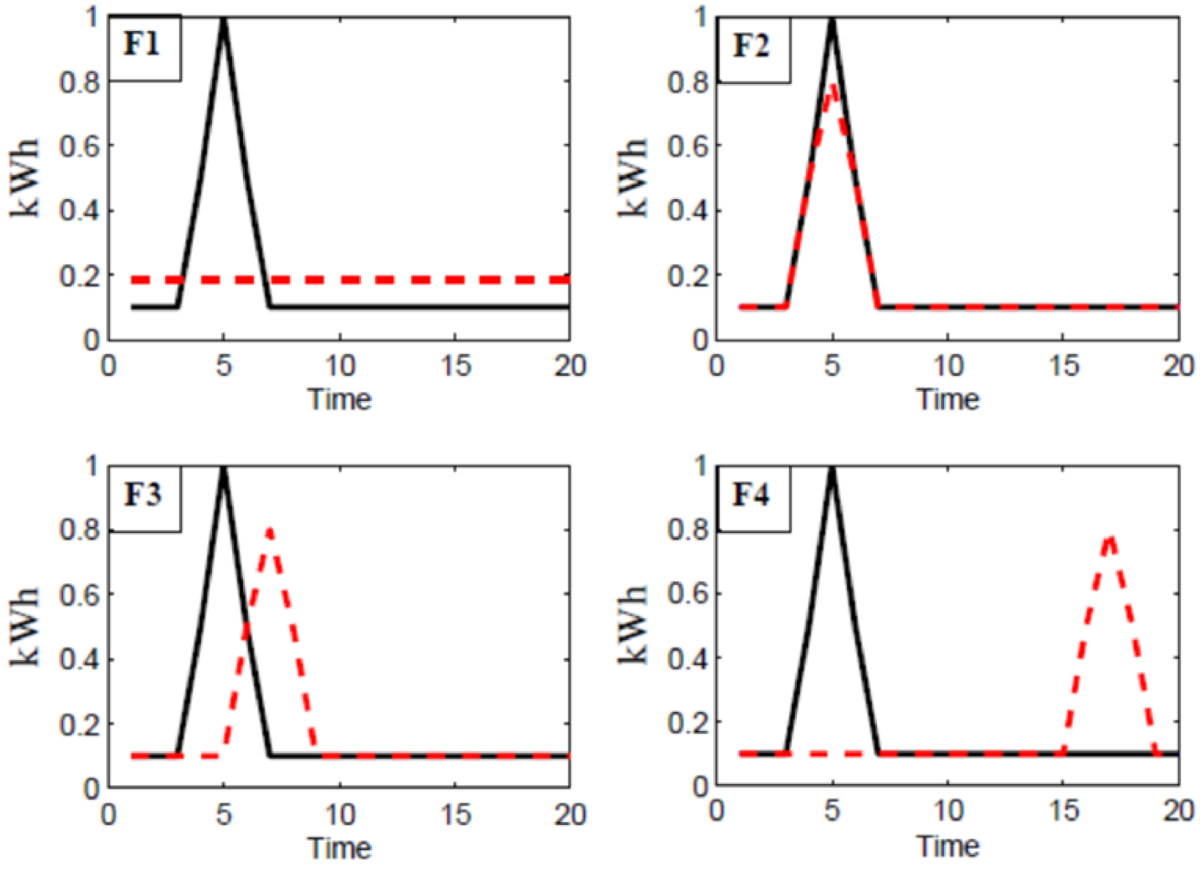
Picture courtesy Billiejoe Charlton

Adjusted Error

$$E_p^w = \min_{P \in \mathcal{P}} \|P\mathbf{f} - \mathbf{x}\|_p$$

How about allowing a small adjustment of the larger peaks? Then we can measure with a standard error measure.

	Forecast			
Error	F1	F2	F3	F4
Absolute Error	0.82	0.20	0.99	1.00
Adjusted Error ($w = 1$)	0.82	0.20	0.79	1.00
Adjusted Error ($w = 2$)	0.82	0.20	0.48	1.00
Adjusted Error ($w = 3$)	0.82	0.20	0.20	1.00

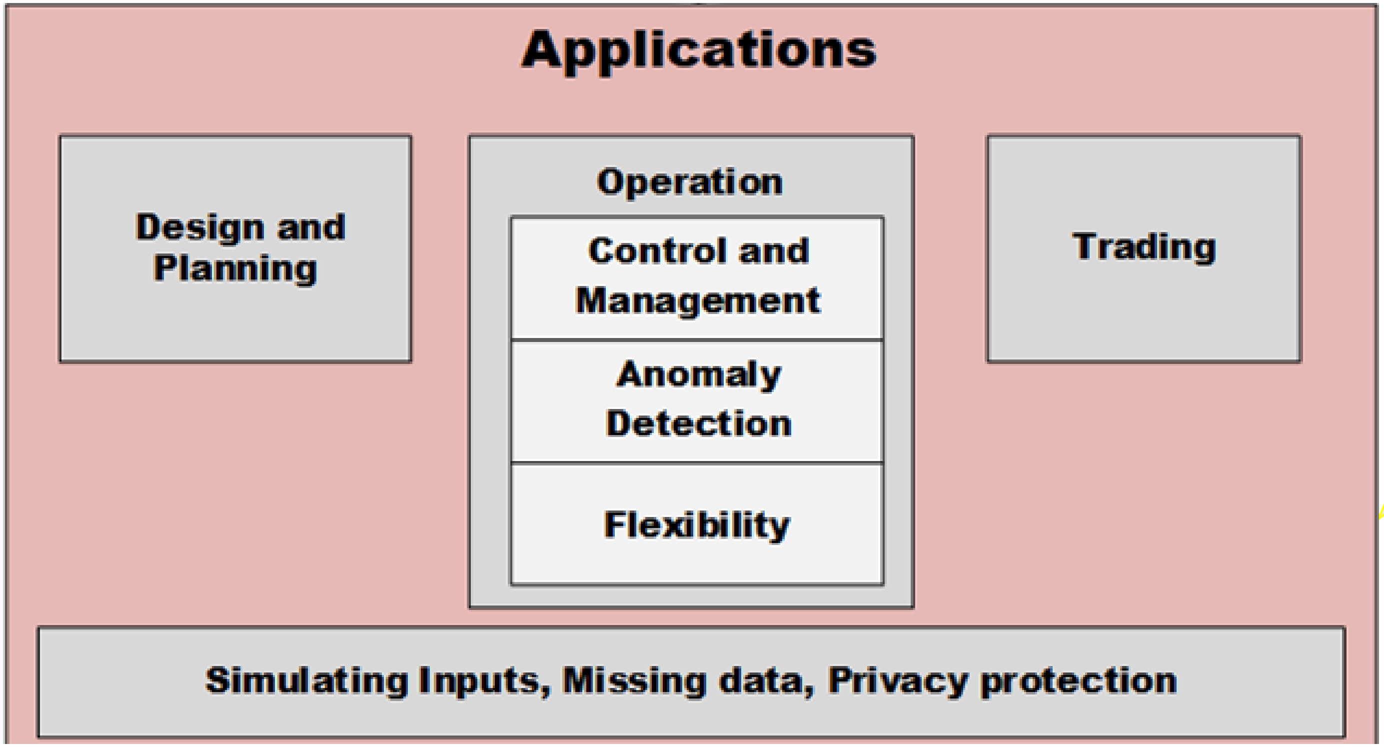


WHAT ARE THE MAIN CHALLENGES FOR MODELLING AND FORECASTING LV NETWORKS

- Difficult to model and optimise due to:
  - Lack of data
  - LV does not scale up easily
  - Heterogenous, Volatile (smoother easier to predict)
  - Unclear boundaries – what to include and what to ignore (e.g., temperature)
  - Lot of effort on higher voltages and homes (e.g. Big Tech data centers solutions, etc)
  - Small and medium enterprises left out
  - Applications often ignore forecasts features

WHAT IS A GOOD FORECAST? IT DEPENDS… ON APPLICATIONS.

Different applications will require different forecast features.



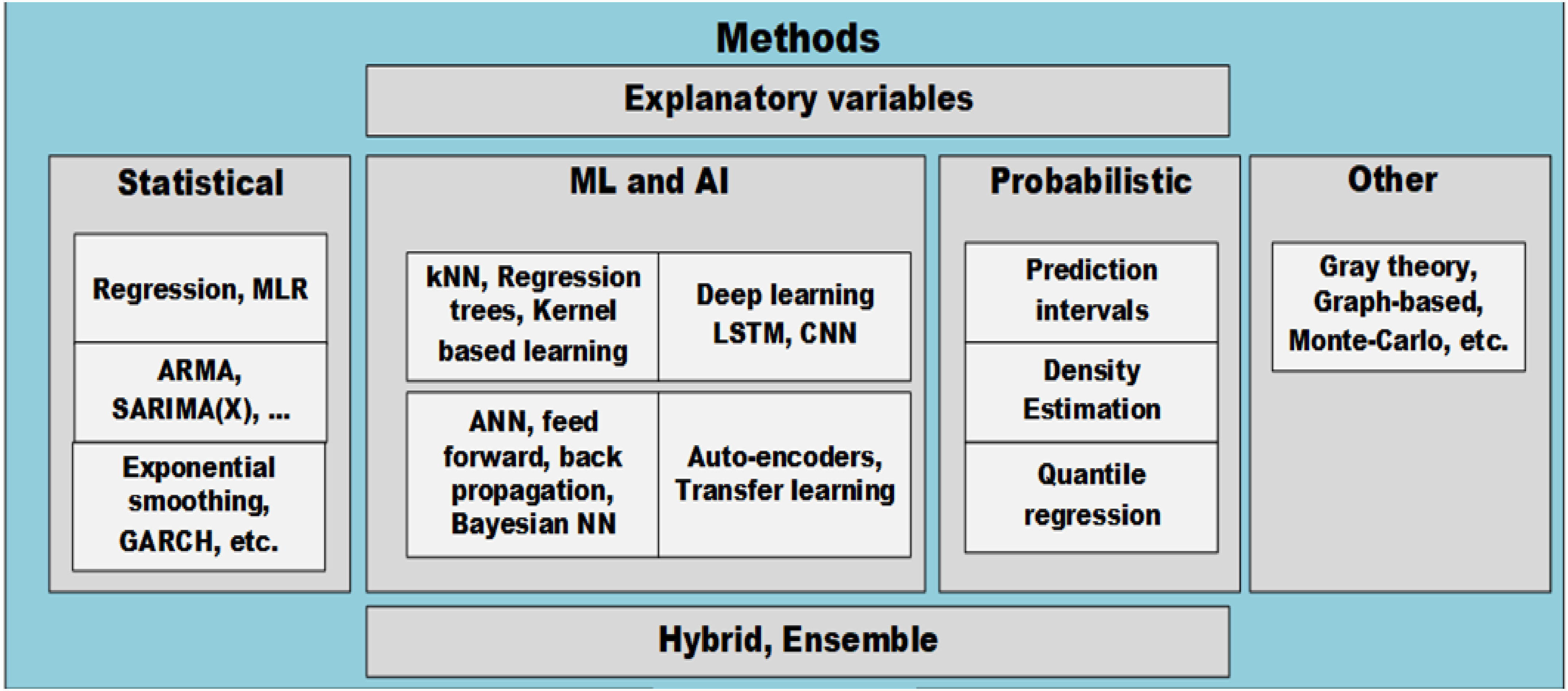
WHAT IS A GOOD FORECAST?

- Real time or offline ?
- How important is accuracy (point or confidence intervals?
- Peak accuracy?

However, it is not always taken into account what impact different forecast features (e.g. accuracy) will have on those applications…

Haben et al. (2021), **Review of low voltage load forecasting: Methods, applications, and recommendations,** *Applied Energy, Volume 304, 2021, https://doi.org/10.1016/j.apenergy.2021.117798*.

WHAT CAN WE THROW AT IT? THIS AND MORE…



STILL NEED TO WORK ON...

Methodological challenges

Data

- Limited number of datasets available
  - Privacy issues
  - Bias

Forecast skill

- Peaks/error measures

Features

- No SOTA - different applications might require different approaches
  - Probabilistic forecasting/ Understanding uncertainty for decision making
  - Deep learning/Trust/ Explainability

- Real time or offline ?
- How important is accuracy (point or confidence intervals?)
- Peak accuracy?
- Distribution assumptions?
- Horizon?
- Skill?
- Aggregation level?

MIND THE (RESEARCH) GAP(S)

What have we found ?

A lot of noise, i.e. papers lacking

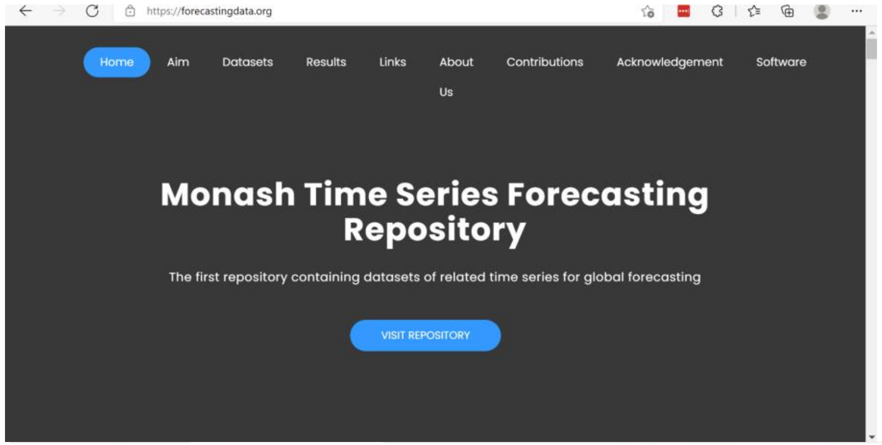
- ❖ Reproducibility (no datasets or code available)
- ❖ Accessibility (language/lack of precision)
- ❖ Benchmarks (affecting evaluation, but also innovation)

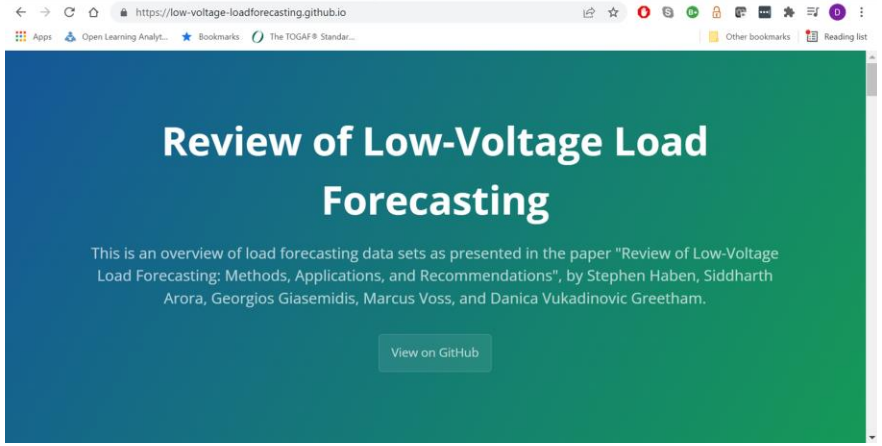
“

Out of 221 papers, only 52 use at least one openly available datasets to illustrate the results, i.e. less than 24%) Of these 52 papers using open data,

- 22 (or 42%) of them used the Irish CER Smart Metering Project data,
- 4 used data from UK Low Carbon London project,
- 4 from Ausgrid4 and
- 3 used the UMass dataset.

In other words, out of the papers using open data, 56%, presented results that used data from only four open data sets…





WHAT ARE THE TRENDS?

- Data preprocessing, feature and parameter selection agnostic to the forecasting method applied, clustering, evaluation of different forecasting methods
- Real-time methods, online forecasting based on data-streams and sensor data

Automation

- Categorise load (filter based on signal processing or similar) and combine or adjust methods
- Use classification or regression to split

Divide and conquer

- Double penalty
- Local Permutation Invariant distance
- Adjusted Average

Evaluation/ error measures

WHAT ARE INDUSTRIAL GAPS?

- Data collection on LV level challenging
- Data management maturity lags (FAIR-ification of data still to happen)
- Privacy and security challenges

Data

- Knowledge transfer from academia challenging
- Important features might differ for different LVs
- Evaluation of models hard (different applications with different needs)

Models

- Data and model governance challenging
- Lack of trust in ML solutions
- Usually significant customisation of models needed (difficult to scale up)

Productionisation

SO WHAT?

RECOMMENDATIONS

- Improving access to literature
- Tackling single-source data bias
- Towards clarity in problem definition
- Need for benchmarks and robust validation
- Privacy
- Better understanding of forecast features in applications
- Use of Computational Intelligence Models
- Modelling uncertainty due to weather
- Moving towards probabilistic forecasting

THANK YOU!
ANY QUESTIONS?

THANKS TO

Siddharth Arora, University of Oxford

Georgios Giasemidis, independent researcher

Marcus Voss, Birds on Mars & TU Berlin