Forecasting research initiatives

25 August 2021 FRG Meeting

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Background and Purpose

This presentation provides the background to the Forecasting Research Plan, and includes an overview of current research initiatives and a discussion of future research needs.

Engagement timeline

FRG Timing	Details
Oct 2020	Forecasting Enhancement Research Project
July 2021	2020 Forecast Improvement Plan progress update
Today	**Forecasting research initiatives**
Oct 2021	2021 Forecast Accuracy Report with draft Forecast Improvement Plan

Today's agenda:

- Rationale and approach for research
- Relationship between the Forecasting Improvement Plan and research
- The NEAR program
- Initial view of Forecasting Research Plan
- Example projects:
    - Demand traces
    - PV rebound
    - Spatial demand drivers

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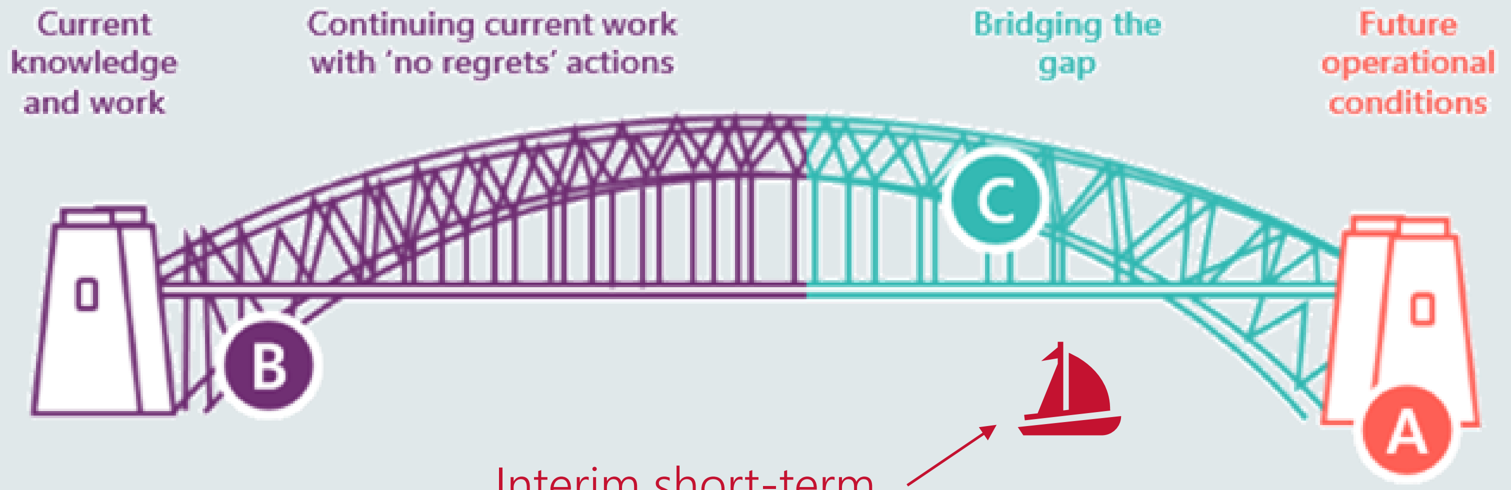
Research helps us do things better – and prepare for future challenges

2 Our current forecasting state (capabilities and knowledge).

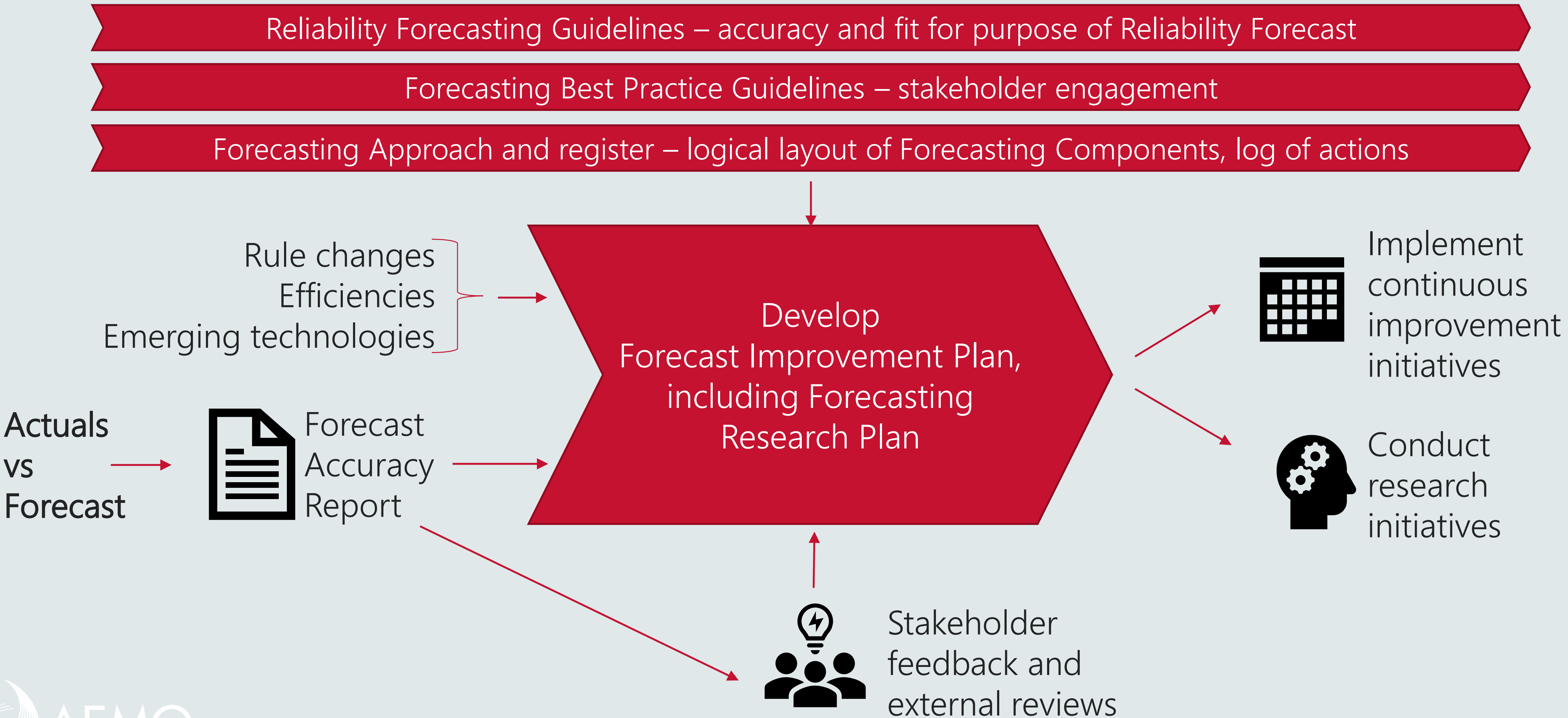
3 The Forecasting Research Plan takes us from B to A, prioritising capability and knowledge gaps, considering required timeframes, and managing the research risk.

1 The forecasting target state (capabilities and knowledge) is informed by
- AEMO strategy
- Planning and engineering studies
- Stakeholder feedback



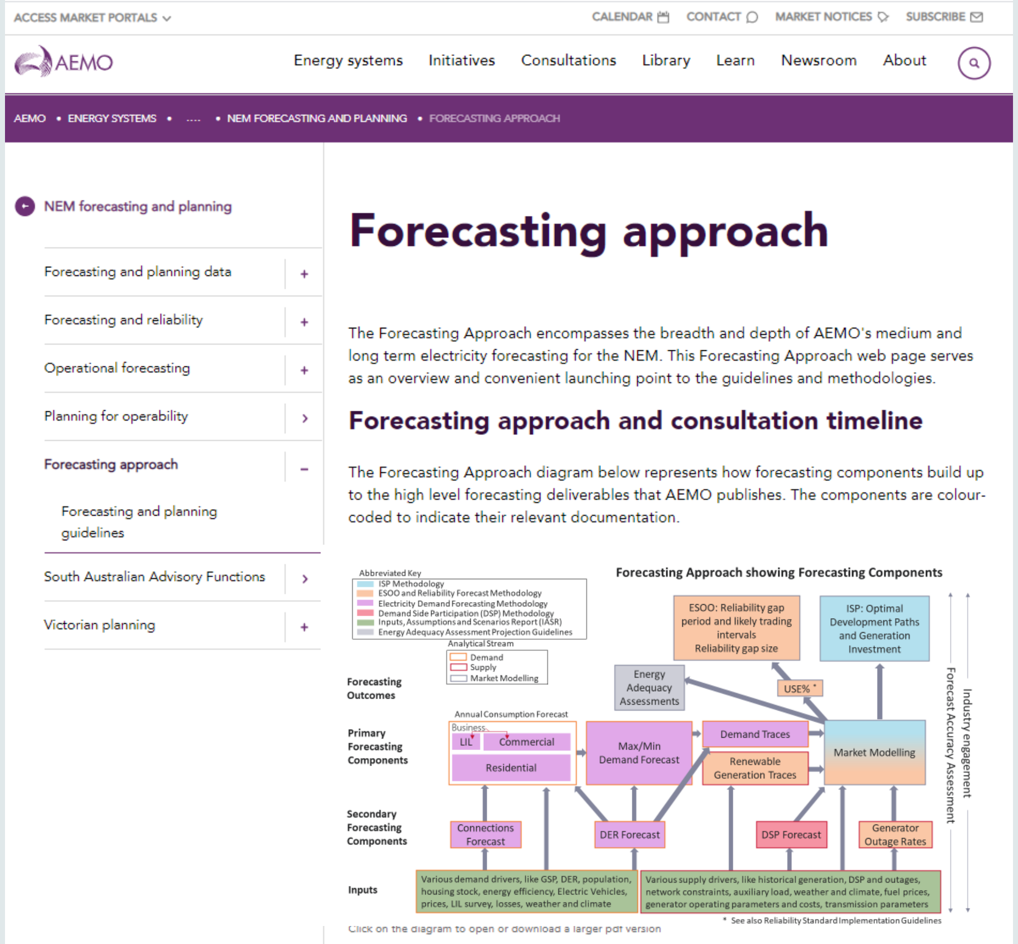
Interim short-term solutions can be considered.

The Forecast Improvement Plan guides AEMO's ongoing technical improvements



Forecasting Approach Register

- The Forecasting Approach Register summarises and responds to:
  - Matters raised outside formal consultation processes.
  - Feedback on AEMO's Forecasting Approach and consultation timeline.
  - Actionable feedback on how AEMO engages with stakeholders on forecasting matters.
- The register will therefore pick up ideas for actioning, including the potential for research initiatives.



https://aemo.com.au/en/energy-systems/electricity/national-electricity-market-nem/nem-forecasting-and-planning/forecasting-approach

Independent review

- Stakeholder submissions to the Electricity Demand Forecasting Methodology sought independent review of forecasting methods; added to the Forecasting Approach register.
- AEMO has commissioned a consortium of Melbourne, Monash and Deakin Universities to undertake a review of its demand forecasting methods, to evaluate the:
  - Appropriateness of current methods;
  - Existing trade-off between accuracy and explainability;
  - Ability of existing methods to work in the medium term, as the power system transforms.
- The consortium will report back to FRG at end of project (early 2022).
- The report is to include suggestions for future research.

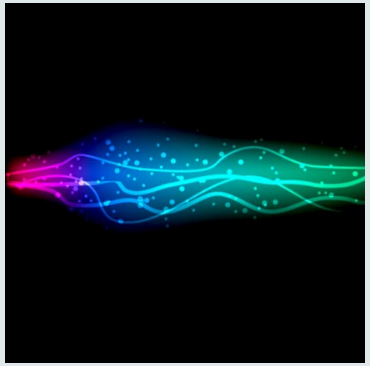
Research is progressed within AEMO and in collaboration with others

In assigning research, AEMO seeks to balance expertise, data access, availability and costs

Research name	Researcher	Goal
NEAR (National Energy Analytics Research)	CSIRO	Collect, integrate and enhance energy sector information for use by researchers, the public and industry participants. The project website https://near.csiro.au/ publishes • PV data • Zone substation data • Tools for data visualisation and exploration • Profiles of energy consumers • Consumption by Local Government Area (LGA) • Heating and cooling data
EV distance travelled modelling	UTS	Short study completed Dec 2020 on EV usage patterns in a North Sydney case study. Shared with CSIRO and influenced charging profiles and hence CSIRO's EV forecast.
Data centres and EV fast charging	AEMO	Ongoing use of meter data to research growth in data centre consumption (growth within existing, and new centres) Ongoing use of meter data for identified fast charging sites to validate fast charging profiles

The NEAR program delivers a data platform to inform energy analysis and research

- The NEAR Program brings together data from across the energy sector, establishes pathways for improved data publication and sharing, and executes data research to unlock new value from both existing and emerging data assets. It is an extension to the previous Energy Use Data Model (EUDM) program and is currently funded by Department of Industry, Science, Energy and Resources (DISER).
- It is a collaboration between DISER, CSIRO and AEMO.
- Program website: https://near.csiro.au/
- Example of NEAR projects completed in 2020-21:
  - Identification of behind the meter batteries
  - Temperature sensitivity of demand
  - Data centre consumption
  - Commercial building baseline study
- Example projects planned for 2021-22:
  - Spatial demand drivers
  - Behavioural change in consumption following installation of PV
  - BASIX review



Interactive data visualisations

Making PV gross again

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Initial view of Forecasting Research Plan

- AEMO has so far identified the following areas of forecasting improvement opportunities:
  - Multi-sector modelling
    - Improve alignment of AEMO's forecasting models with inputs from economy-wide integrated assessment modelling (IAM).
  - Future load shape & traces
    - Understand changes in future load shape from technology uptake, customer incentives and climate change/extreme weather events and reflect this in a larger number of generated load traces.
  - Spatial Demand Forecasting
    - Improve modelling of spatial demand drivers (both at connection point and subregional level).
- The 2021 FAR, the stakeholder feedback to the FAR, and the independent review, may flag additional opportunities.

- Today three specific projects are highlighted:

PV rebound | Spatial demand drivers | Demand traces

PV rebound

Behavioural changes in consumption of owners of rooftop PV systems

Magnus Hindsberger; AEMO

Nariman Mahdavi; CSIRO

Growth in observed peak demand – does PV rebound have an impact?

- In recent years, observed winter peak demand has increased in many regions. For the current winter, for example, we have seen to date:
  - NSW: Highest winter peak since 2010
  - SA: Highest ever winter peak (second year in a row record set)
  - VIC: Highest winter peak since 2011
  - WA: Highest ever winter peak
- A similar trend can to a lesser extent be seen for summer.
- This can be driven by a number of reasons, such as underlying demand growth (driven by population and the economy) and changes in consumption patterns following COVID-19.
- Another potential driver for this could be the so-called 'rebound effect' from owners of PV systems.

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What is the rebound effect?

Rebound effect: Users taking advantage of a new lower price of the energy service to use more of that service (typical example is to have a warmer home after efficiency improvements).

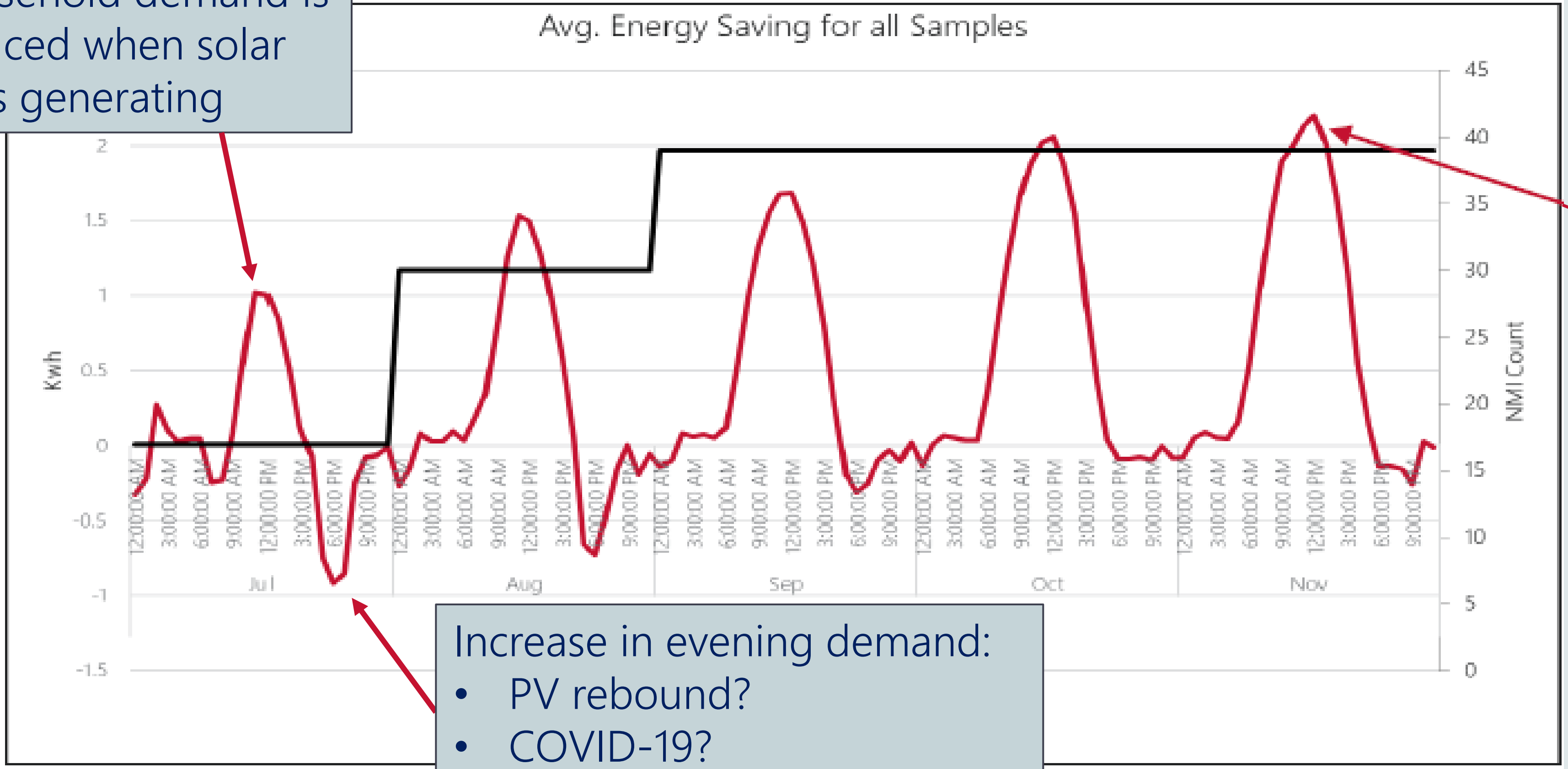
A rebound effect of 20% reflects that only 80% of the expected consumption reduction is achieved.

- The rebound effect is well known phenomenon within energy efficiency policy area, but applies similarly to other initiatives that lowers the perceived price of electricity for customers.
- Typically, rebound effect is measured at an annual level, but can equally be used to assess change in customer demand at various points in time, for example typical peak demand hours (or min demand periods).

Numerous studies have assessed the rebound at an annual level, with a typical value of around 20%.

Focus of NEAR study is to understand time-of-day solar rebound

Household demand is reduced when solar PV is generating



From September onwards energy savings increase as spring brings more solar irradiance

Increase in evening demand:

- PV rebound?
- COVID-19?
- Too small sample size?

Source: AEMO

Rebound effect in the literature

- Rebound Effect essence (Energy Economics): true savings << potential ones
  - Jevons (1865), Khazzoom (1980): unintended consequences

- In household with PV modules
  - Keirstead (2007): UK survey data, self-assessed 5.6% electricity saving
  - Wittenberg (2016): DE questionnaire to prosumers & consumers
  - Deng (2017): AU billing data sample prosumers & consumers; 20% rebound
  - Oberst et al. (2019): DE small sample prosumers & consumers
    - Electricity consumption proxied by heating expenses
    - No significant prosumer effect, no rebound
  - Boccard & Gautier (2019): BEL large prosumers sample; meter readings
    - PV estimated by capacity factor
    - Oversized group: +35%; undersized group: -4%

Approach/ Research Questions

- PV installation date Y
- PV rebound effect calculation:
  - Mean daily consumption (Q) over a year before/after installation date
  - $Q(t<Y) =$ meter reading
  - $Q(t>Y) =$ net meter reading + PV estimation
  - $\Delta Q = E[Q(t>Y)] - E[Q(t<Y)]$

- How accurate is the PV estimation using capacity factor?
- What are the effects of different social demographics?
- What is the effect of ambient temperature change?
- What if we use Min/Max instead of Mean?

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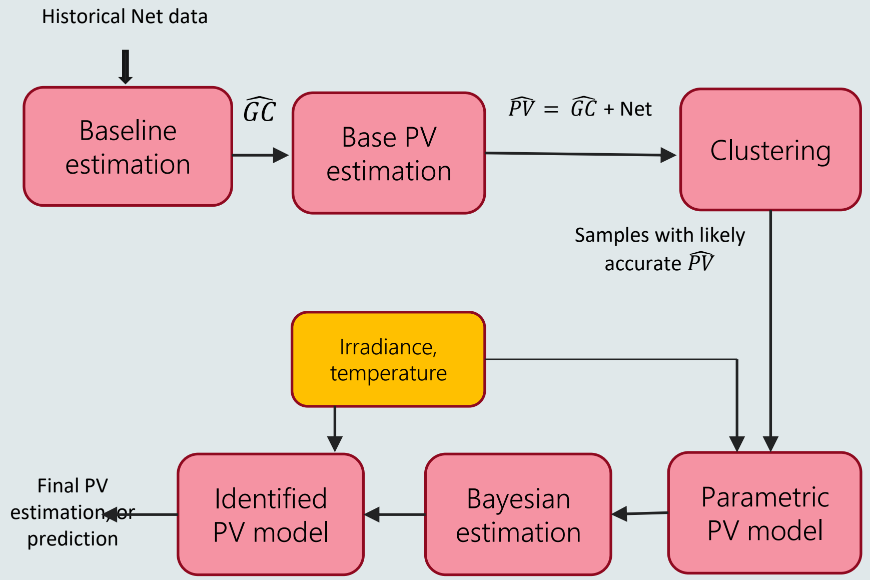
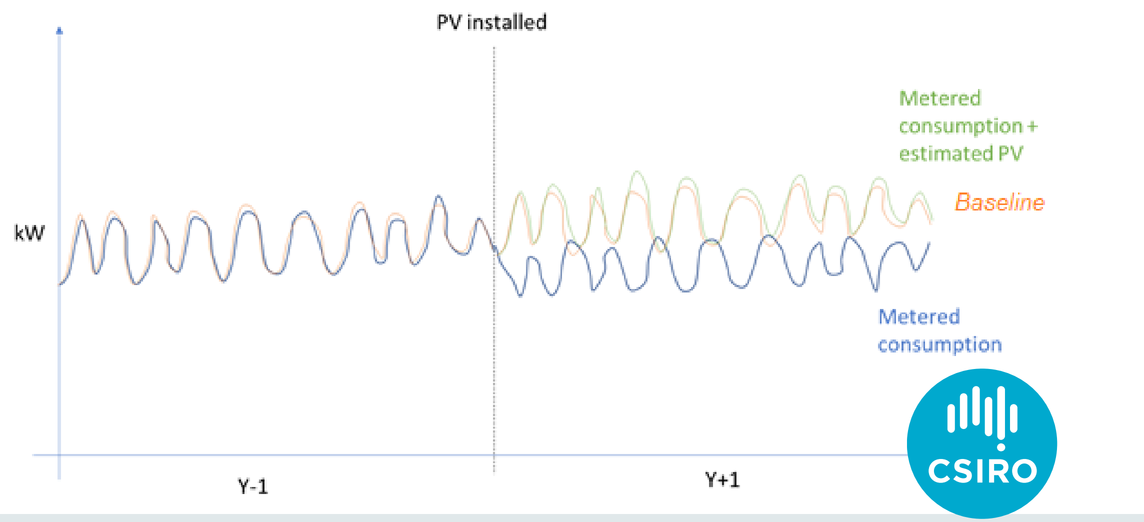
What’s new?

- Behind-the-meter PV estimation
- A baseline instead of Q(t<Y)
  - Baseline is the last year consumption adjusted by temperature
  - Include a set of representative load profiles based on day type/season/temperature
- Calculations at individual scale, then aggregation at Postcode
  - Different demographics less likely to affect
  - Different PV installation dates won’t be an issue
- Min/Max/Mean demand change over year/month/weekday/weekend
- Determining the contributing factors (including Covid) is out of scope





What's next?

- Access to AEMO environment with
  - PV installation dates of households in a given postcode
  - At least a year smart meter data before/after installation date, for all households with PV
  - Temperature/solar irradiance data linked to a postcode
- Run our algorithms on AEMO lab and getting the outputs
- Targeting a solar rebound estimate for typical max and min demand times, by June 2022

Spatial demand drivers

Identifying optimal set of forecast drivers for connection point and subregional demand forecasts

Magnus Hindsberger; AEMO

Ying Guo; CSIRO

Seeking improvements in driver choice for spatial forecasting

- AEMO typically forecasts demand at regional level (for the ESOO and ISP) and connection point level (for more detailed network planning studies)
- Compared to its regional demand forecasting approach, AEMO currently uses basic growth drivers in its connection point forecasts.
- Project purpose: develop a method to identify optimal spatial demand drivers. Example:
    - Typical residential-dominated connection point's demand is driven by population, PV and work patterns (time of day, day-type)
    - Typical industrial-dominated connection point's demand is driven by economic factors.

In addition to connection point level, the method should also work at subregional level

2022 ISP will use a subregional representation of the network rather than regional (as used in the 2020 ISP)

Figure 4 Regional representation of the NEM, including existing interconnection

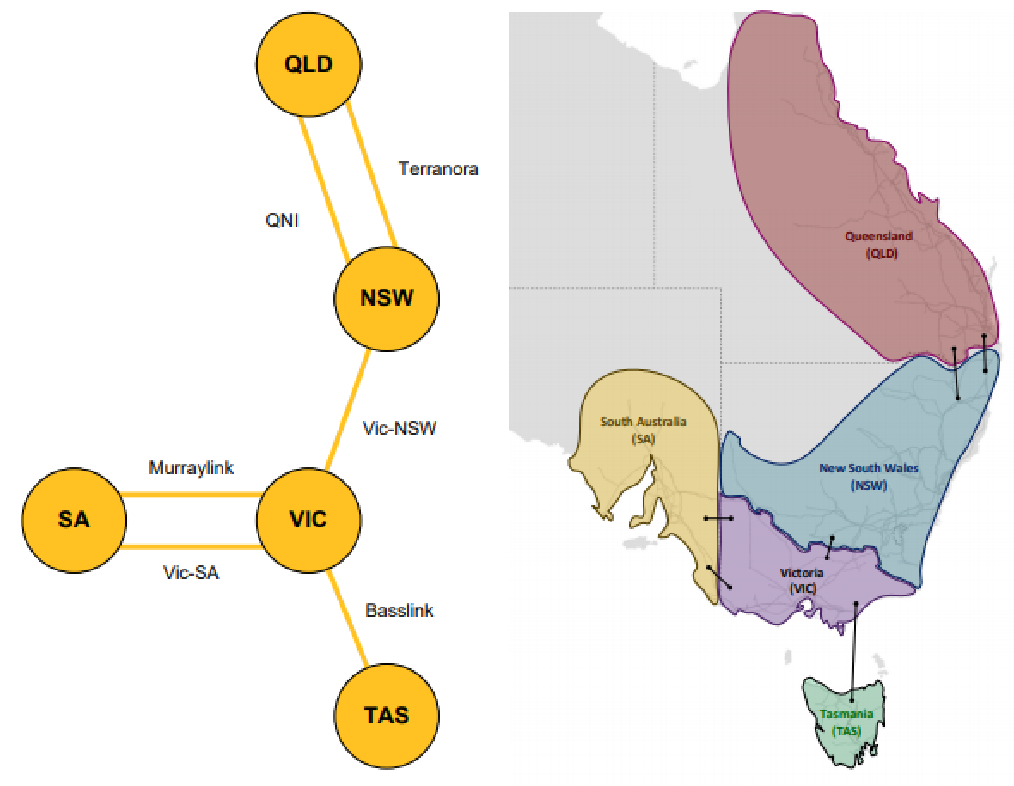
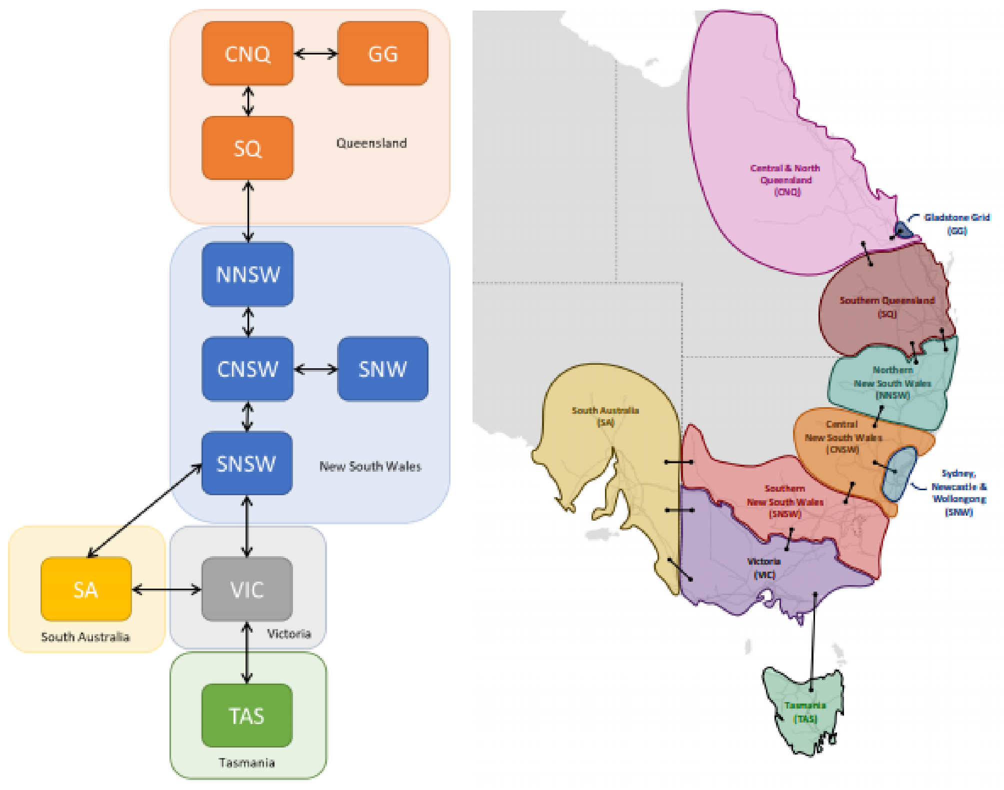


Figure 5 NEM sub-regional topology



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https://aemo.com.au/-/media/files/major-publications/isp/2021/2021-isp-methodology.pdf

Timing of Spatial demand drivers research

Propose methodology for selecting datasets.

Propose an assessment of primary and additional data set selection.

Report the assessment results.

Finalise list of datasets that will be used as candidates.

Draft methodology for identifying drivers.

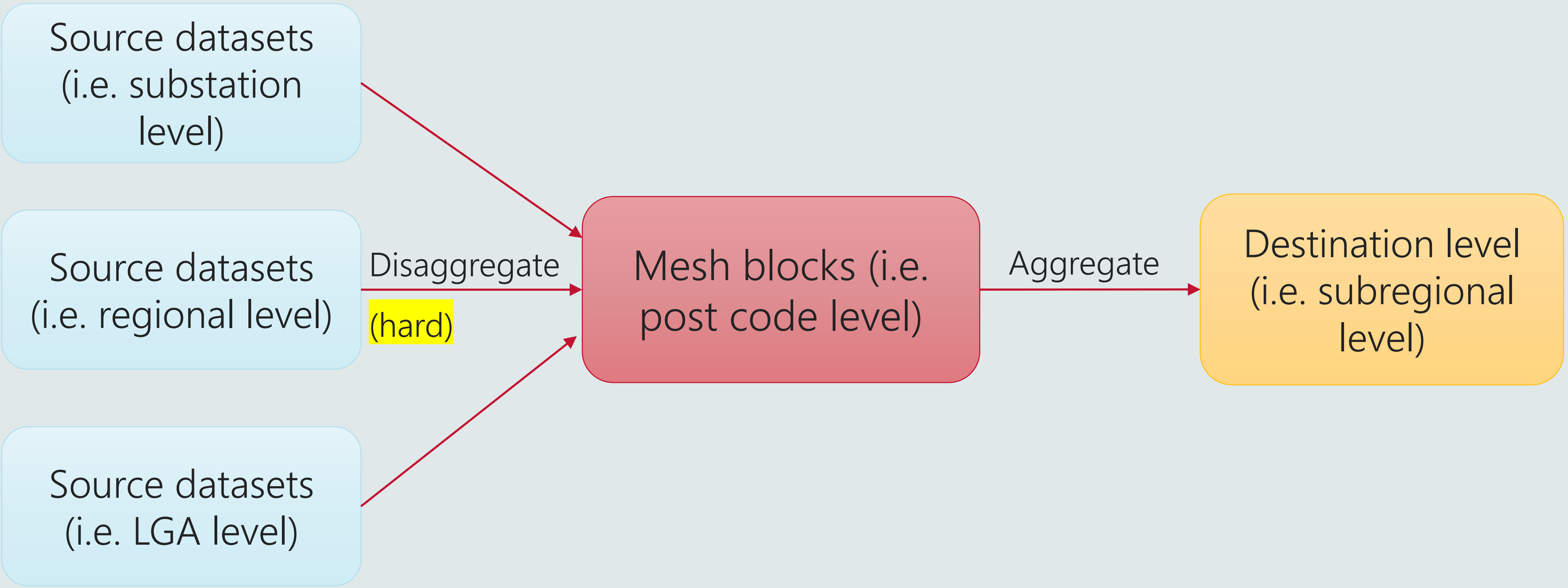
Implement methodology for selection of key drivers.

List of draft drivers for demand at connection point.

Final methodology for selecting drivers for demand forecast.

June 2022

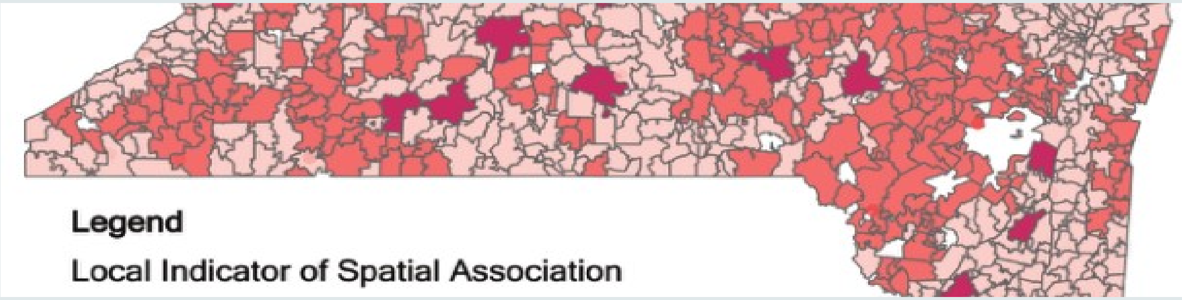
Process spatial data sets from multiple sources, assess them, and identify potential list



Possible data sets: population (ABS, LGA), Gross State Product GSP (ABS), Electric vehicles (CSIRO), Energy Efficiency (AEMO), etc.

Potential methodology for identification of spatial demand drivers (1)

- Most data sets have (potential) geographical elements. Some suitable spatial perspective (regression) approaches are:
  - Spatial regression[1]: modelling the local or spatial spill-over effects from neighbour units (i.e. subregions), and calculate the spatial autocorrelation values.

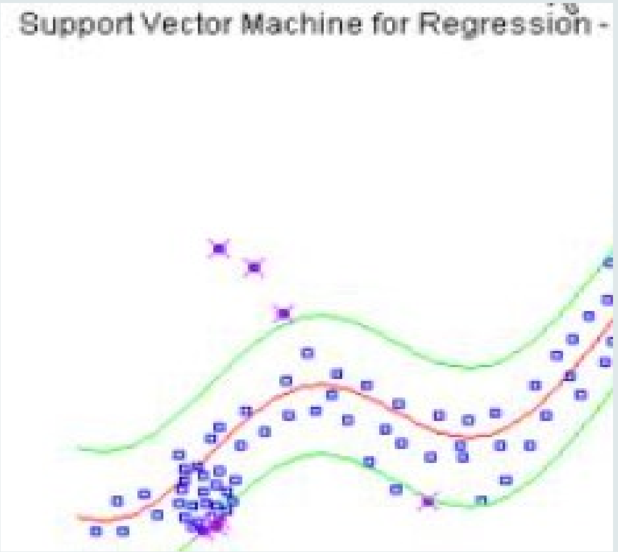


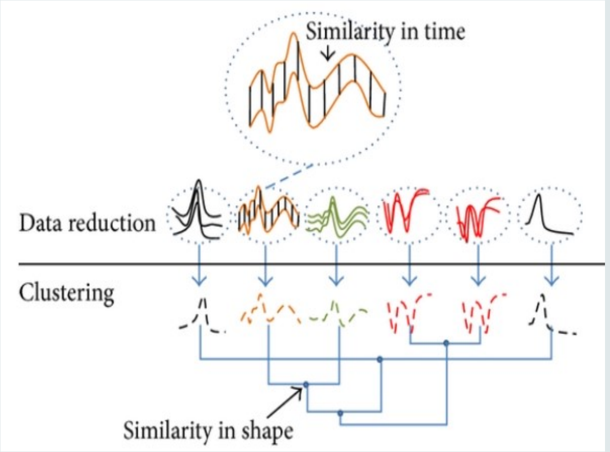
  - Dynamic Common Correlated Effect approach (DCCE)[2]: allow unobserved common factors to be possibly correlated, and calculate the coefficients among data set and targeted variable.

[1] Joseph Nyangon & John Byrne (2021) Spatial Energy Efficiency Patterns in New York and Implications for Energy Demand and the Rebound Effect, Energy Sources, Part B: Economics, Planning, and Policy, 16:2, 135-161
[2] Meo, M.S., Sabir, S.A., Arain, H. et al. Water resources and tourism development in South Asia: an application of dynamic common correlated effect (DCCE) model. Environ Sci Pollut Res 27, 19678–19687 (2020).

Potential machine learning based approaches

- Non-linear regression modelling for geographically related elements:
  - Support Vector Regression
  - Genetic algorithms
  - Hidden Markov Models
- Clustering algorithms for time series elements (i.e. daily community mobility report (where residents spend there time) from google)
  - Shape-based clustering problem with Complexity-Invariant Distance (CID),
  - Fast Global Alignment kernels (non-linear): $K(x, y) = \langle \varphi(x), \varphi(y) \rangle$





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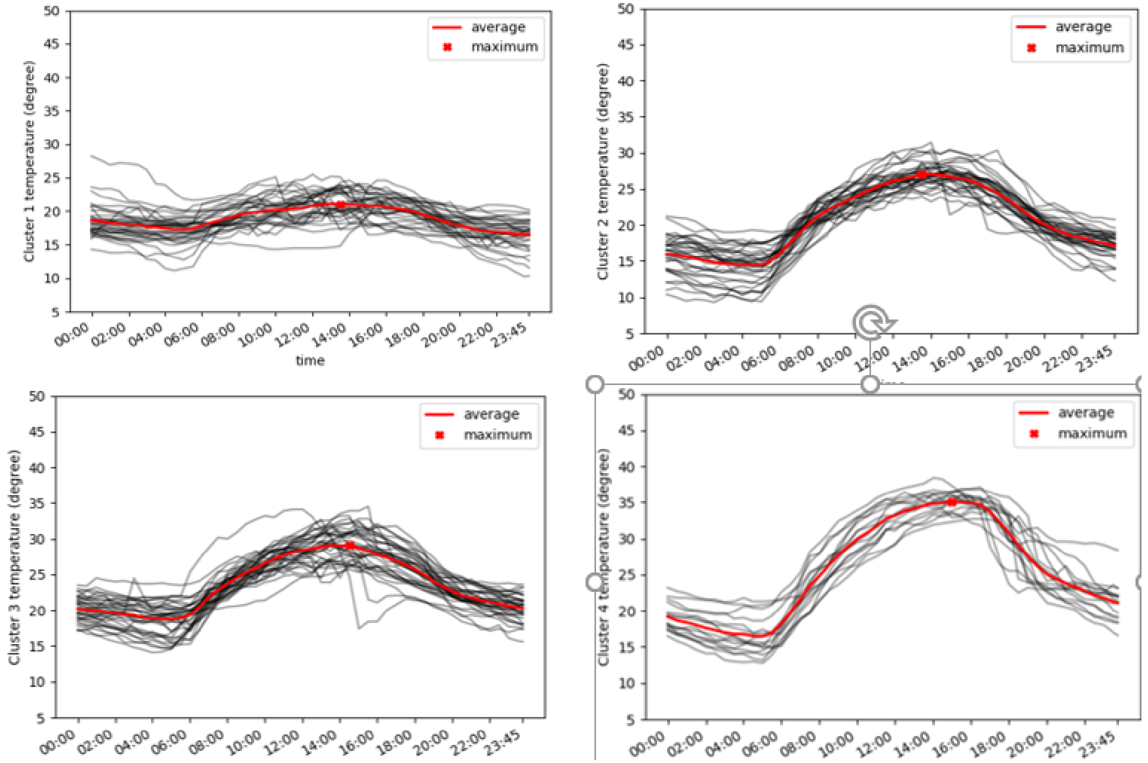
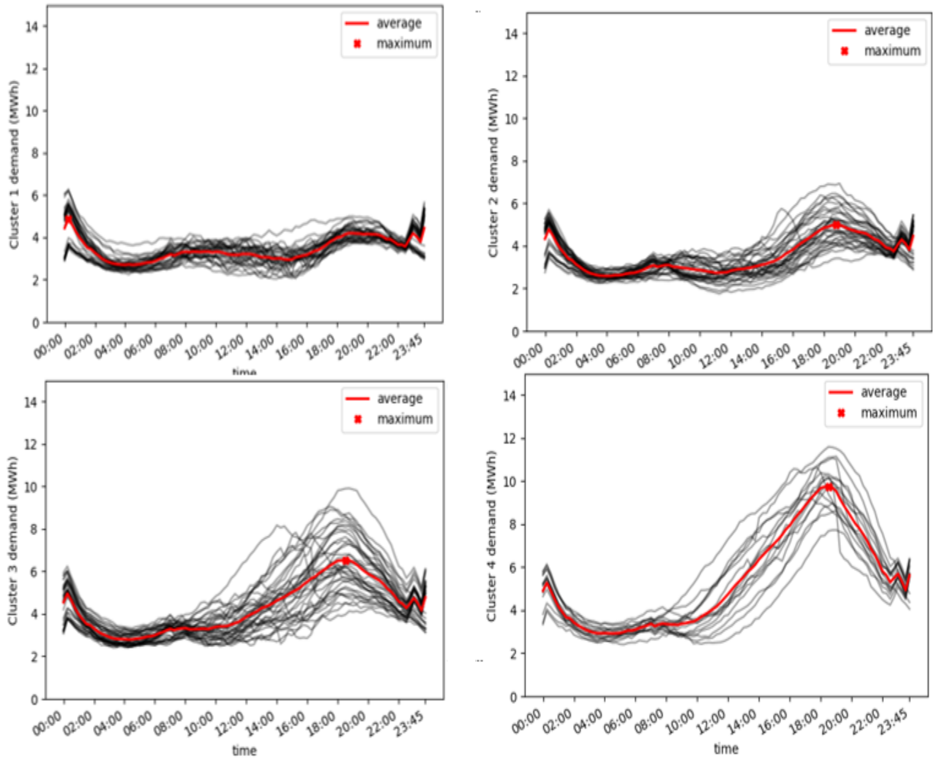
Example of clustering results of temperature, and the correlated demand

Clustering results of Branxton substation for 2016 summer data (ambient temperature)



Corresponding deman time series of clusters



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Demand traces

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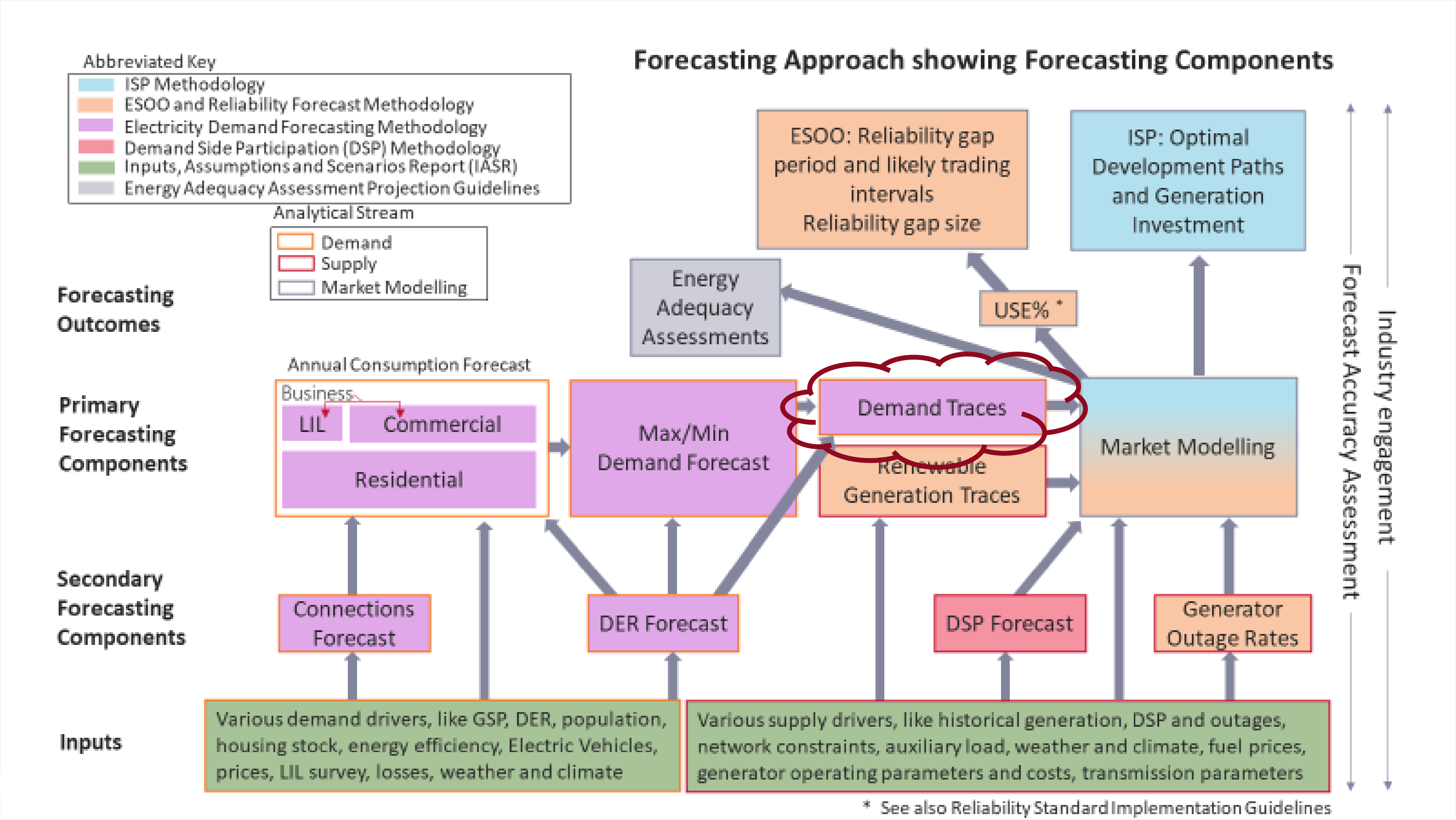
Demand trace generation is pivotal, complex, and sits amidst emerging challenges and opportunities



What do AEMO and stakeholders want from demand traces?

What characteristics are we seeking from current and future demand traces?

- Account for demand generated from weather patterns
  - Both current and future weather patterns
  - Use many more weather years (and corresponding demand traces) in probabilistic forecasts
- Account for temporal demand drivers (day of week, time of day, trend)
  - As affected by new technologies, electrification, etc.

Incorporation of correlation between demand, renewable generation and time. Also, spatially between neighbouring regions.

Intuitive and accessible

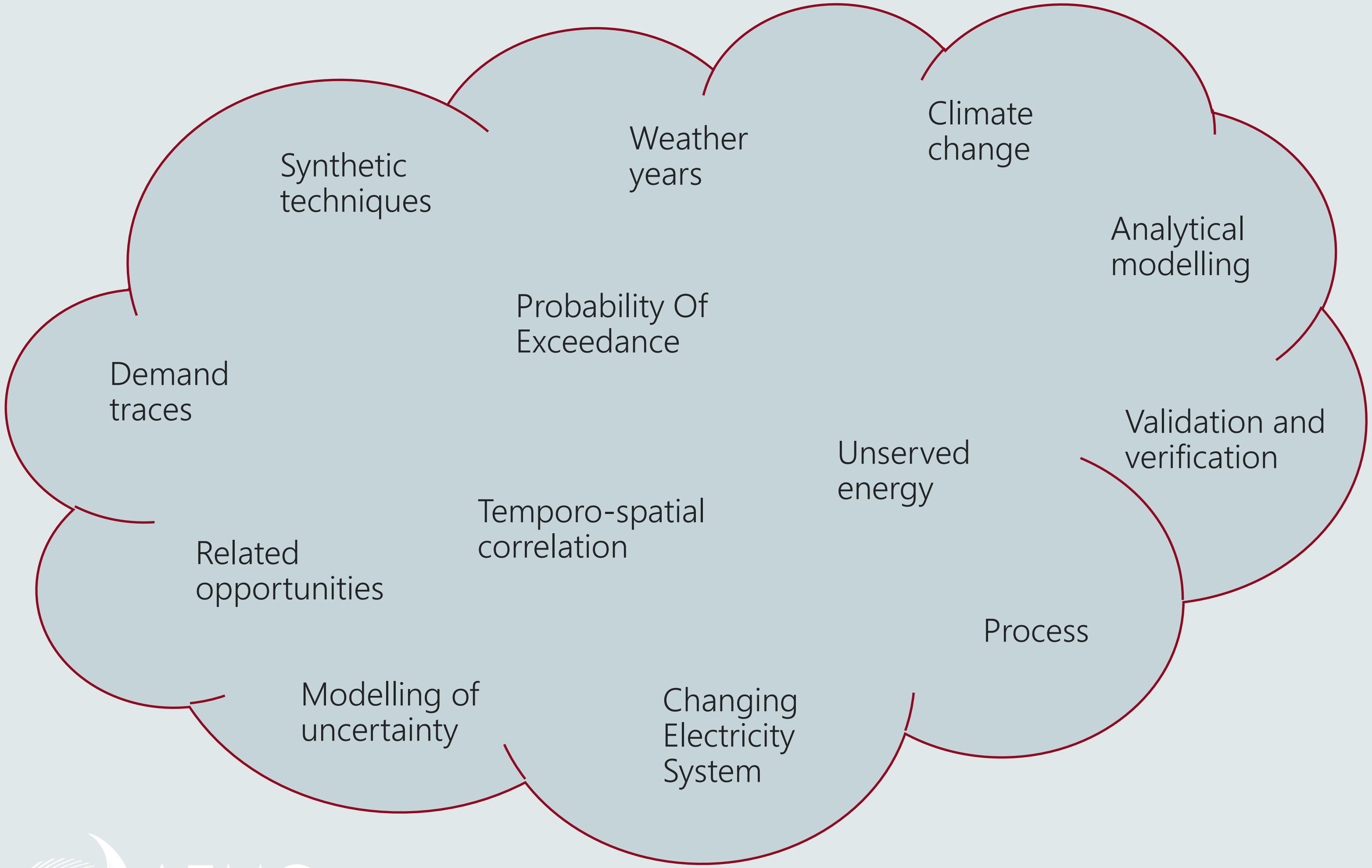
Traces should allow for:

- Calculation of unserved energy in the subsequent market modelling, allowing:
  - Assessment of whether reliability standard is met
  - Identification of problematic timing of generator or network outages
- Identification of scenario-specific future generation and transmission expansion requirements
- Assessment of timing and economics of network investments
- What-if studies, such as:
  - High inverter based instantaneous penetration (mainland NEM) – frequency and duration
  - Ramping events
  - Low coincident renewable generation events such as wind droughts

Will trace approach deliver?

or

The demand trace generation fog! A large and important complexity to be worked through…



Q. How might AEMO and stakeholders best make sense of these topics?

How might AEMO and the FRG best address demand trace generation challenges and opportunities?

Implementation and continuous improvement
Minimum viable product?
Delivery timing

Acceptance criteria
Who can contribute to validation?
What validation would suffice?

Design, Build and Test
What design trade-offs exist?
What are the priorities?

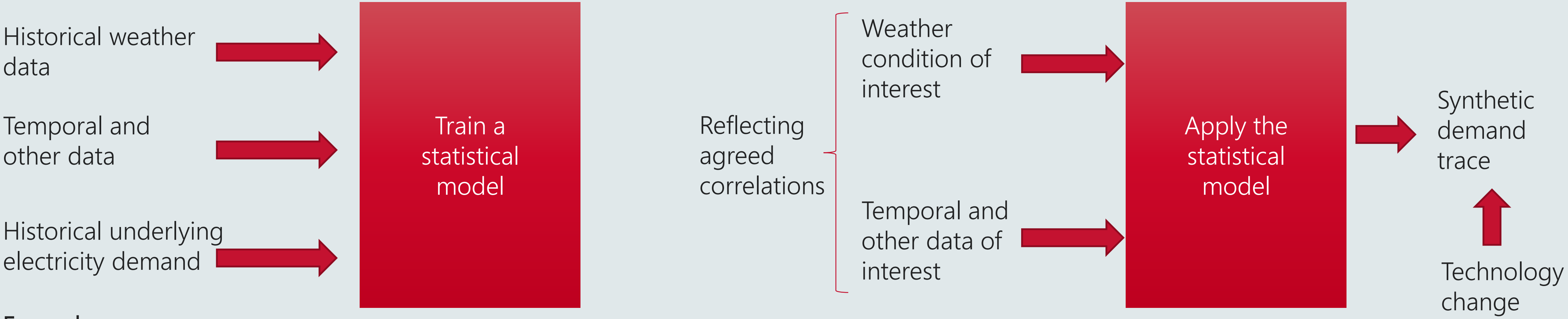
Goals and options
What are requirements for demand traces?
What options exist?
What are synthetic traces?
What goals are relevant?

Why?
What are the problem(s) and the opportunities?
What is the current approach and its challenges?

We are here

Expect complexity and consider who and how to contribute. Sample content: what are synthetic traces?

- Produced from a statistical model of actual data specific to each region, and then estimate demand traces for expected data such as climate change
- The model, like the current model, must reflect complex and evolving interactions of a range of drivers
  - Example: the weather sensitivity of load at 11am on a Monday in December differs from weather sensitivity of load at 11am on a Saturday in June. Additionally, over time, the load sensitivity changes as PV penetration increases
- The model estimates demand for particular circumstances that haven't occurred by interpolating / extrapolating



Example:
Training process determines relationship between Victorian electricity demand at 11am on working December Mondays and temperature, informed from 20 different data points

The model estimates Victorian electricity demand at 11am on a working December Monday at 33'C. Although that circumstance doesn't exist in the training data, 31'C and 34'C did. The model interpolates demand based on relevant actual data, according to identified data relationships.

Let's talk

- Is this presentation's approach to research on the right track?
- Are there any other areas of concern to consider for the research plan or FIP in general?
- Demand traces