THE UNIVERSITY OF QUEENSLAND AUSTRALIA | CREATE CHANGE

Data for Networks

New Insights for Network Operations Using Big Data

Centre for Energy Data Innovation (CEDI)

Centre for Energy Data Innovation

- Research enterprise created in partnership between The University of Queensland and Redback Technologies.
  - AI and Data Analytics
    - Demand Forecasting
    - Non-intrusive Load Monitoring (NILM)
    - Fault detection
    - Safety assessment
    - Consumer feedback
  - Advanced Visualisations
    - Energy dashboards
    - Augmented reality
  - Privacy and Security
    - Smart grid security risks
    - Consent mechanisms for sharing data

A word on data

	High level (Monthly data)	Mid level (30 minute)	Detailed level (1 minute or less)
	Broad management	Data driven	Big data driven
Customers	Market management	Customer Management	Appliance management
Networks	NEM Management	Substation Management	LV Feeder Management
Other	Policy setting	Investment decisions	Real time efficiency
		Consumption (kWh)	Voltage, Current, Impedance, power factor

If you want to take advantage of applications that use streaming data and real-time data analytics to make split-second decisions, you must turn to an end-to-end architectural approach from the edge of physical operations all the way to the cloud.

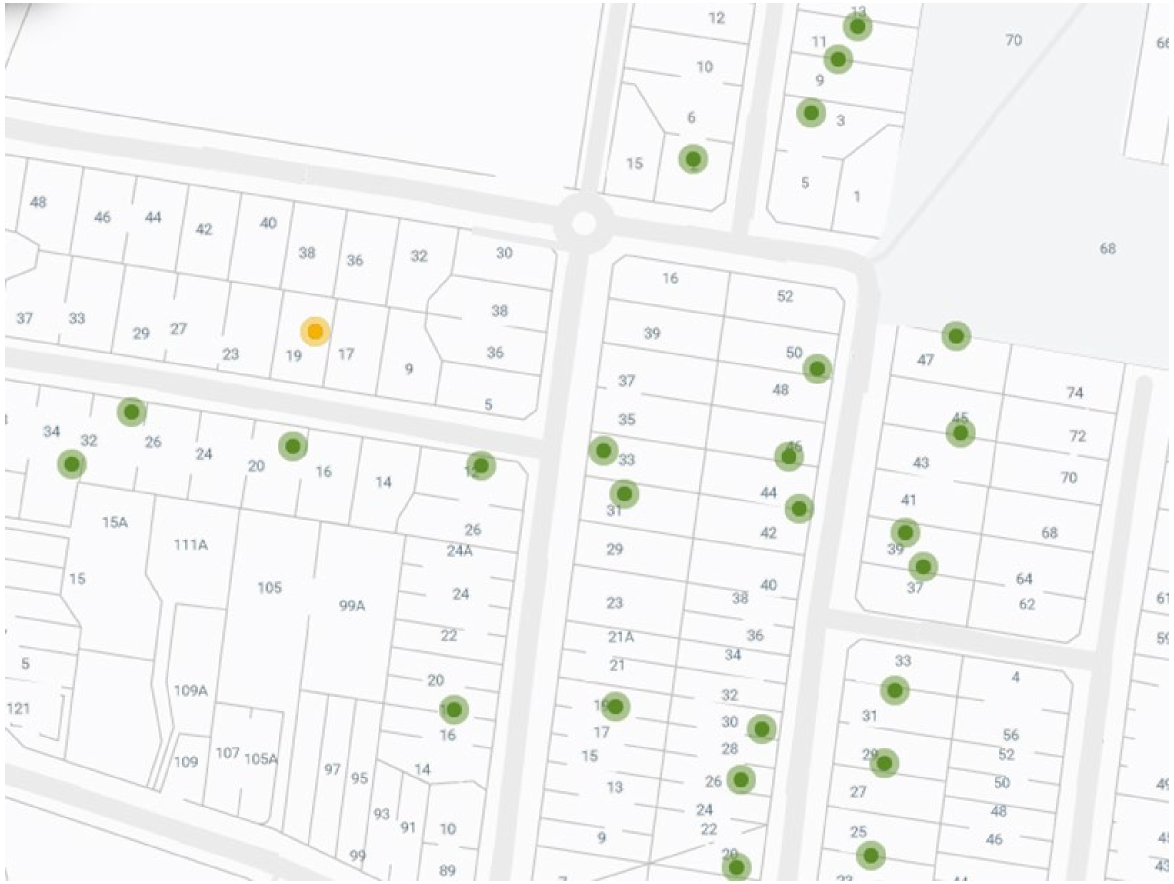
85% of big data projects fail

- They don't bolt on to existing ICT infrastructure
  - Table structures and data formats
  - Data cycle times
  - Scalability of storage
  - Scalability of computing horsepower
  - Security
  - Access policies for users
- Management don't understand or don't want to know
- Lack of skills
- Risk appetite (governance, investment oversight, security risks)
- Scope creep / loss of focus

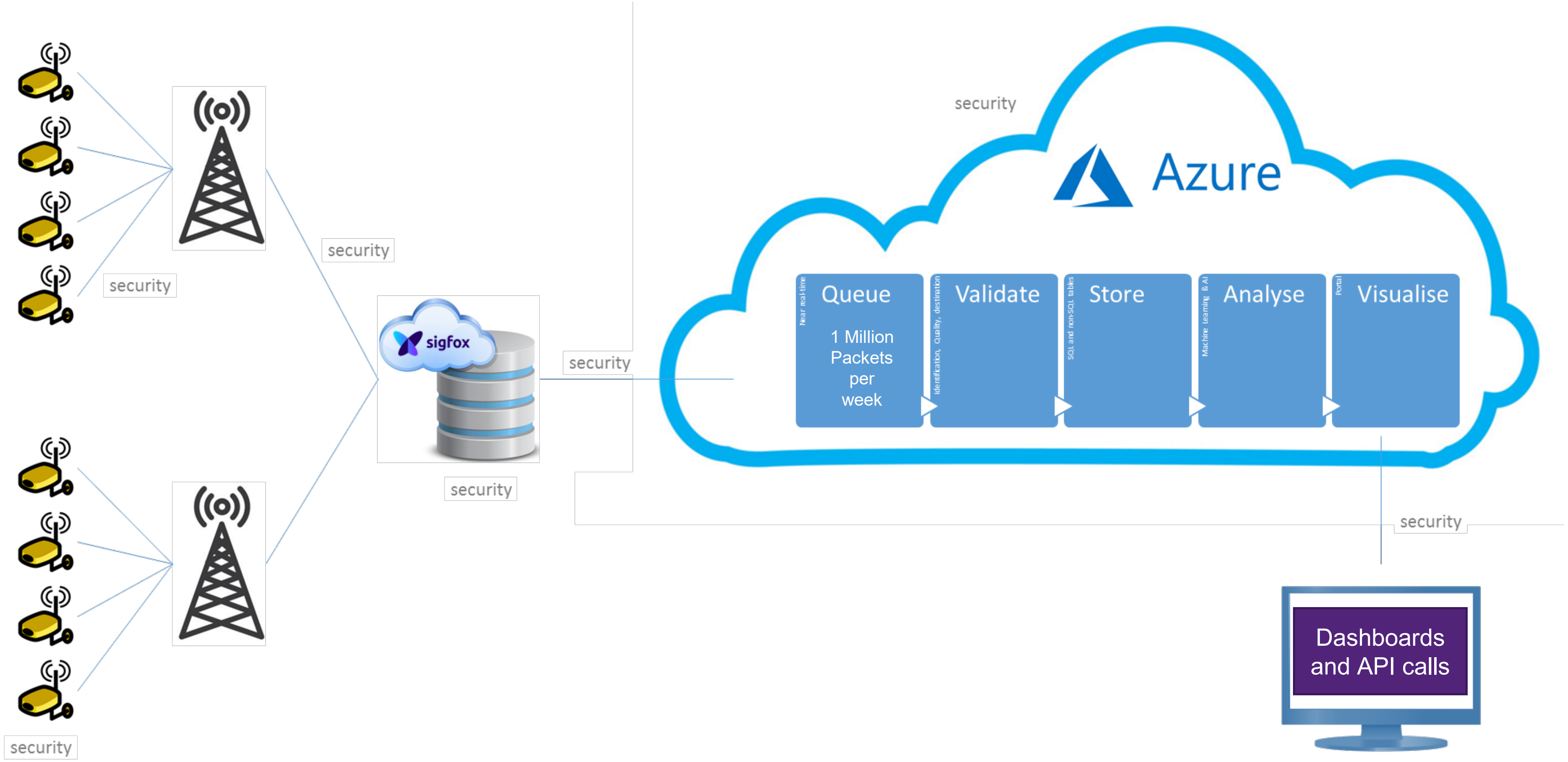
Exploring the physics of LV feeders in real time

Power Data

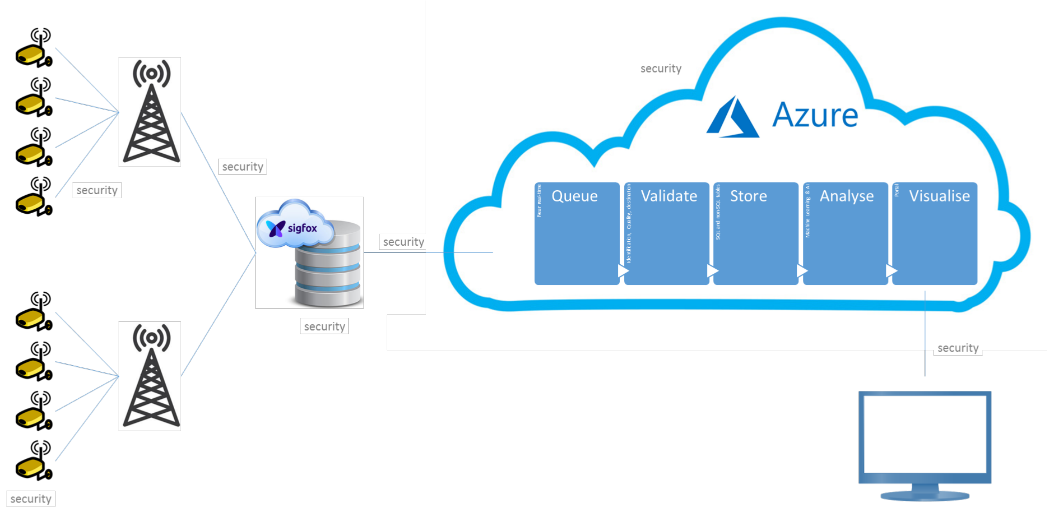
- Current (amps) (import/export)
- Voltage (volts) (import/export)
- Power (watts)
- Impedance (ohms)
- Power Factor



Architecture



Knowledge



Expertise
- Network Engineers (EQL)
- Network ICT (EQL)
- Communications Engineers (Sigfox)
- Software Engineers (Redback)
- Hardware Engineers (Redback)

Research
- Power Engineering
  - Future Grid, Solar PV and Batteries, VPP
- Data Science
  - Platform design and scaling, Data storage and compression, Machine Learning and Artificial Intelligence, Security
- Interaction Design
  - Human-computer interface, CX, Service design, visualisation, AR.

Progress to date

- First 100 devices
  - Understanding the data
  - Understanding the problems (data collection , storage, analysis)
  - Exploring the anomalies
- Opening the Communications channel
  - Ironing out the problems
- Learning about installs
  - Finding room on the panel
  - Accessing meters
  - Asbestos
  - We moved to providing a separate enclosure

- 1st Generation platform
  - User interface designs
  - Scale and pressure testing with Bots
- 2nd generation design
  - Integrating alarms
    - Voltage
    - Broken neutrals
  - User interface customisation
  - API data retrieval

Progress to date

- Next 500 devices
  - Revisiting installation difficulties
  - Expanded data sets
    - 5,000,000 data sets per week
  - Stronger algorithms
  - Business case for step change roll out

- Visualisation
  - Converting data into understanding
  - Workshopping with networks
  - Prototyping substation health indices
  - Exploring AR for feeder interrogation
- Integrating other data
  - Weather data
- Exploring other comms channels
  - 3G, 4G

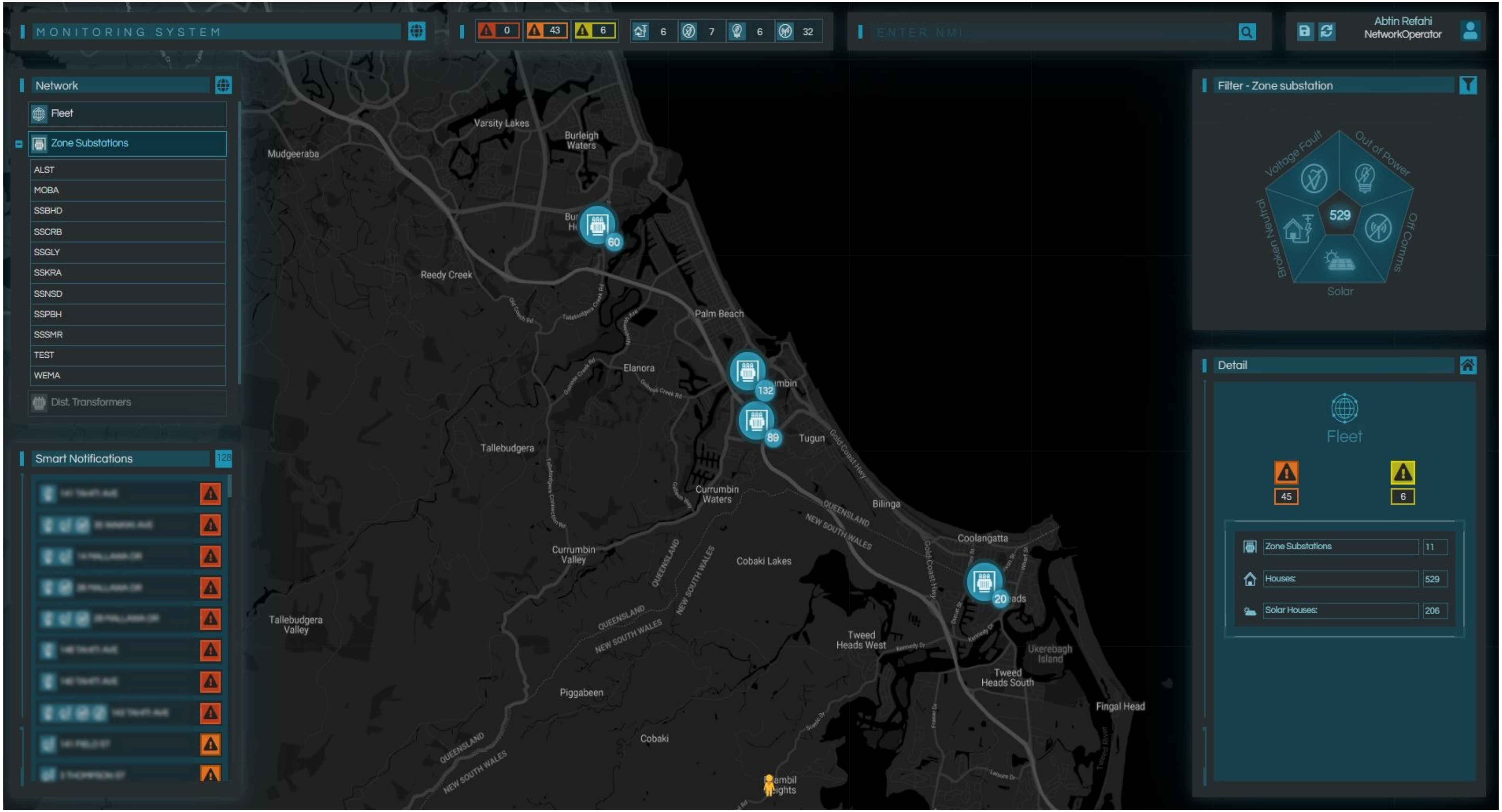
Next steps

- Data step up
  - 20,000 devices
  - 1 million data sets per hour

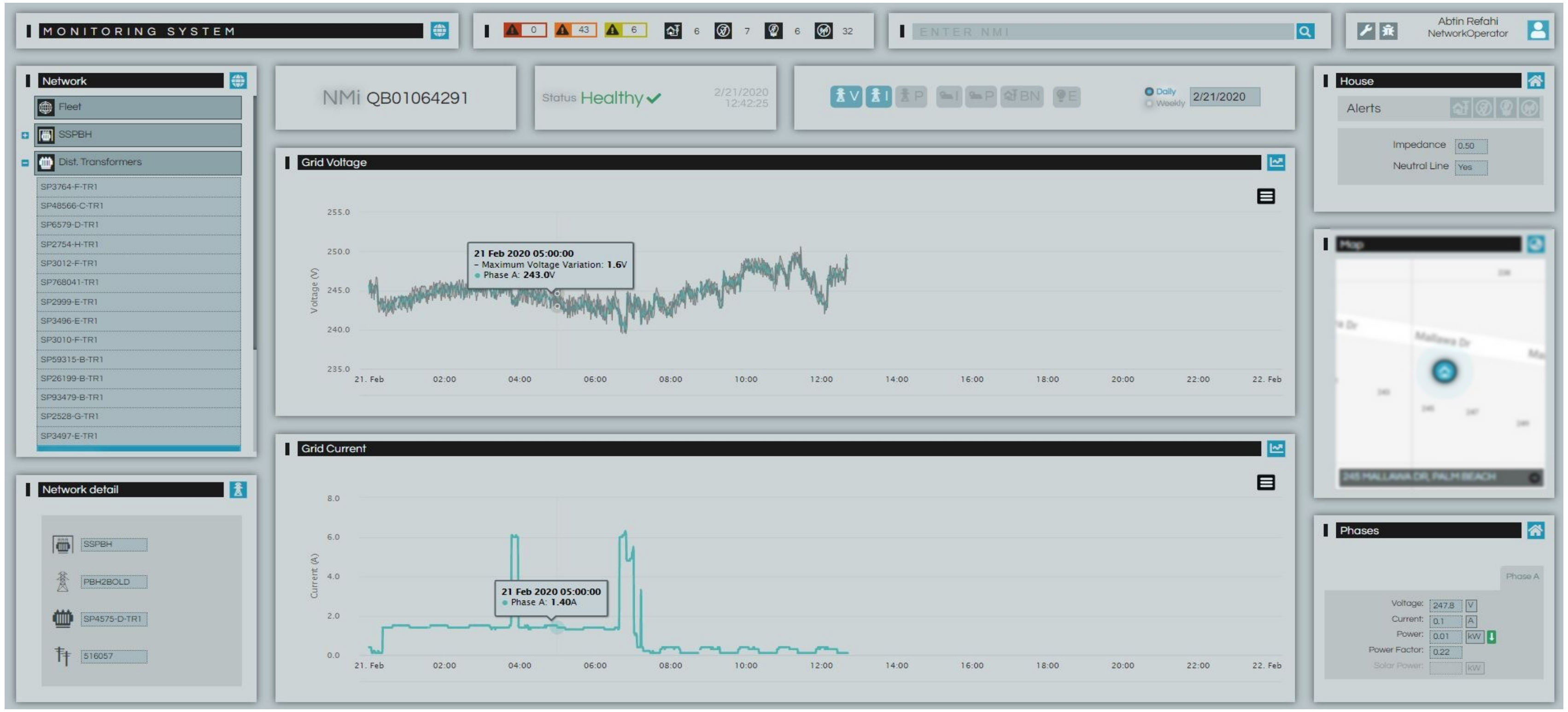
  - Analytics step up
    - Additional broken neutral algorithms
    - Condition monitoring through signal deterioration
    - High impedance faults
    - Supply to life support customers
    - Real time emergency response

- Receiving data from multiple sources
  - Redback Devices
  - Smart Meters
  - Network data
  - Inverters
  - Other?
- New comms channels
  - 3G, 4G

Dashboard view



Dashboard view



Power Data
- Current (amps) (import/export)
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Lessons

1. Lower your risk through collaboration and skill acquisition

2. Be crystal clear what data you are going to collect and why (the customer is paying)

3. Understand the value of real time data versus historical data (cost versus benefit)

Our current focus - Safety

Our initial focus will remain on safety

- Broken neutrals
    - Detected two ways in real time
        - Sub-second sampling and analytics on site
        - Trend detection

Other work

- Phase identification
- Voltage violations
- Forecasting at LV level
- Real time demand management at a household level

Motivations for forecasting and phase ID

- AEMO/DNSP average and peak load forecasts at 10, 50, 90% probabilities of exceedence (PoE) in SoO/APR/APS docs; for simulations leading to business decisions; reserve level studies

Short term forecasting (e.g. hour to day ahead)

- Point forecasting versus probabilistic forecasting
- Virtual power plant, embedded networks
- Battery scheduling – minimizing costs by reducing grid imports at peak times (time of use tariffs)

Medium term forecasting (e.g. month ahead)

- Switching feeders/maintenance
- Based on ensemble weather forecasts (NWP)

Phase identification

- Poor record keeping – home medical device / life support devices
- Large fines - $20,000 – to be avoided
- Phase balancing – reducing losses

Phase identification

Prior research

Pezeshki and Wolf (2012) – correlation based method – “sag and swell”

Using voltage data from houses and transformer

Supervised clustering – three phases, plus transformer data to identify which phase each house was on

Further research – confidence levels around phase ID; costs of phase balancing

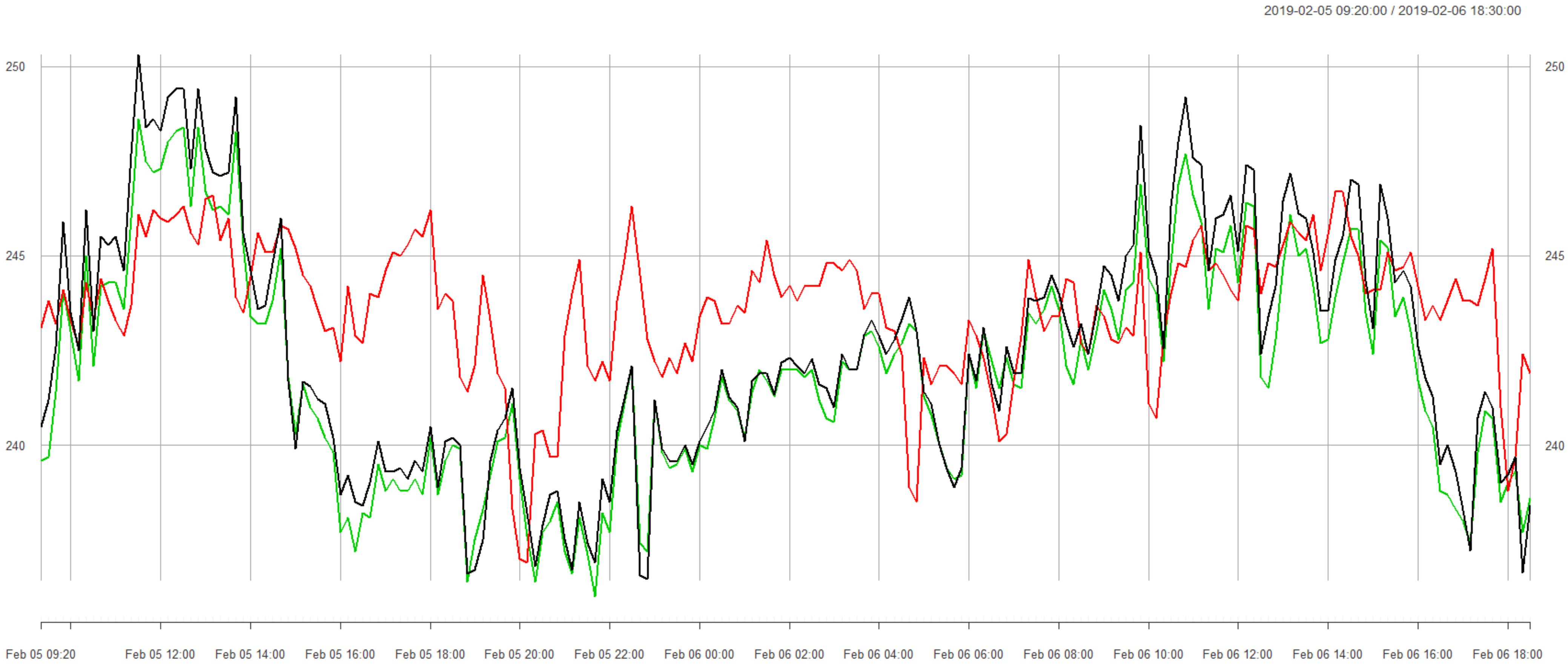
Limited data – good data hard to come by – P & W had 74 houses

Legal obstacles – privacy considerations – addresses/NMIs as identifiers

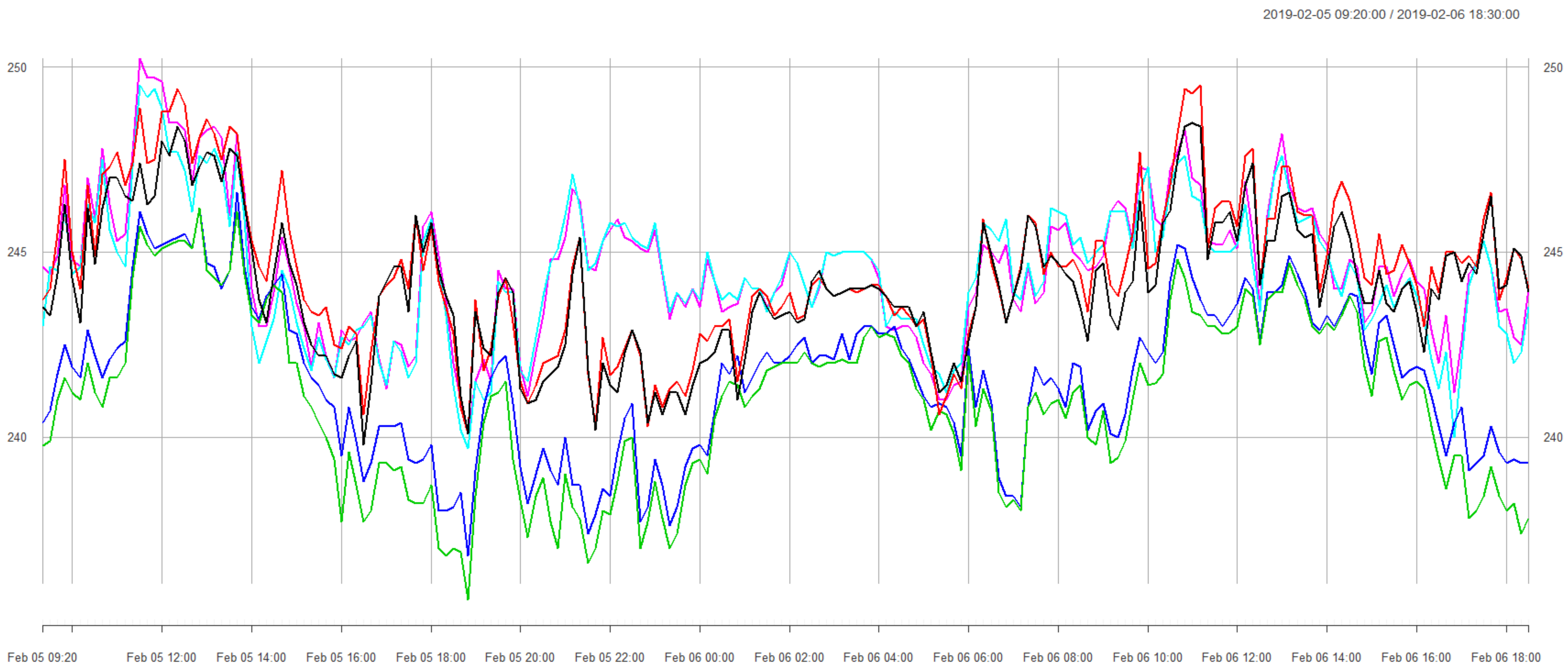
Unsupervised clustering

Can’t identify order of phases (road to house) – more research needed – but aids DNSP to correct existing records

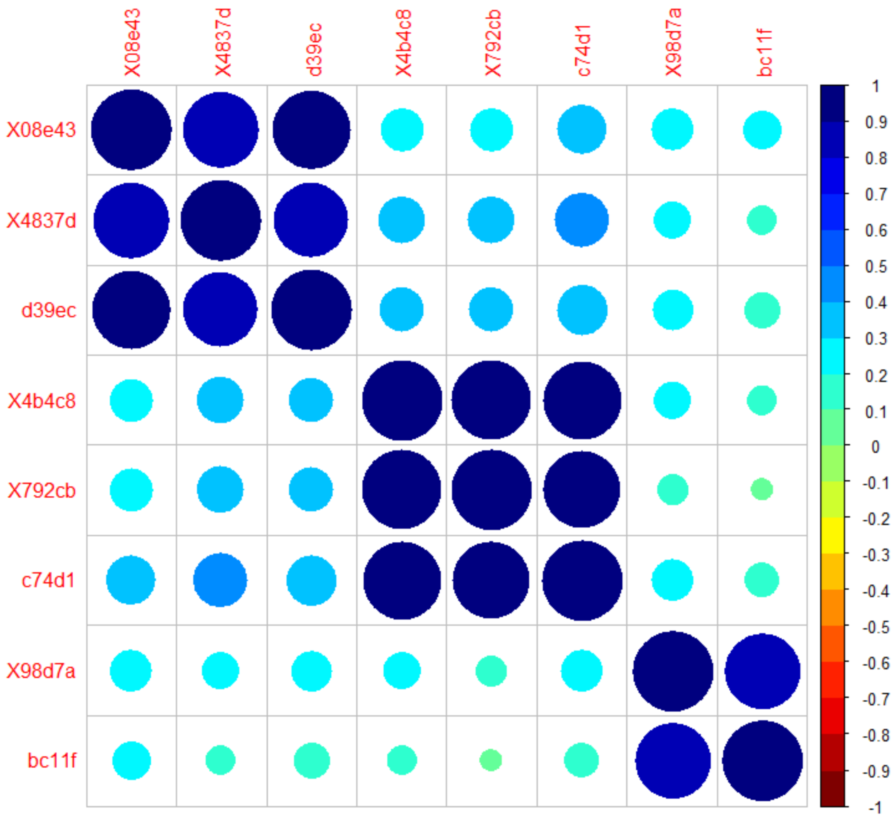
Phase ID time series – 10-minute aggregation



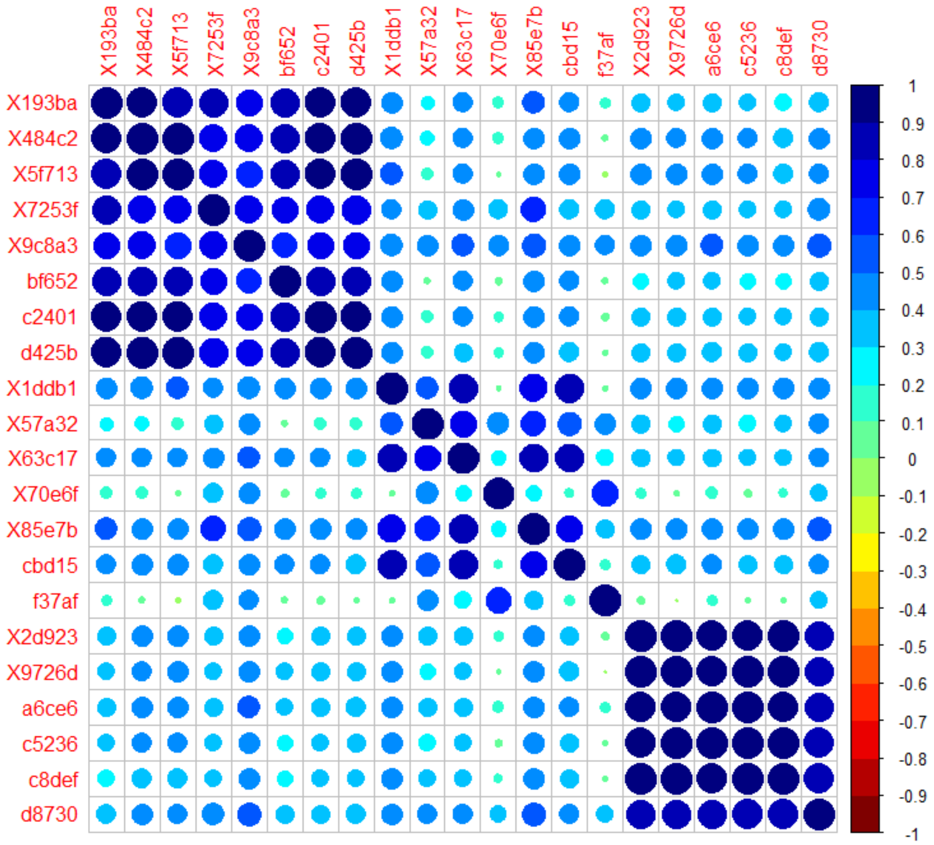
Phase ID time series – 10-minute aggregation



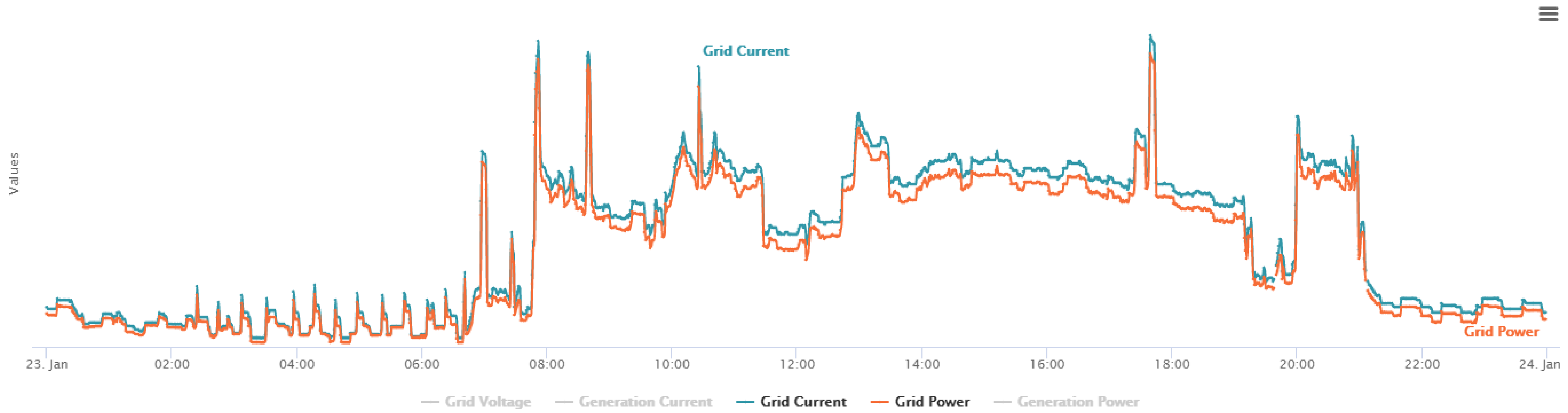
Phase identification – eight houses



Phase identification – 21 houses



NILM - Spot the appliances



Exploring Smart HWS

Data acquisition system workflow:

individually addressable, stores data login

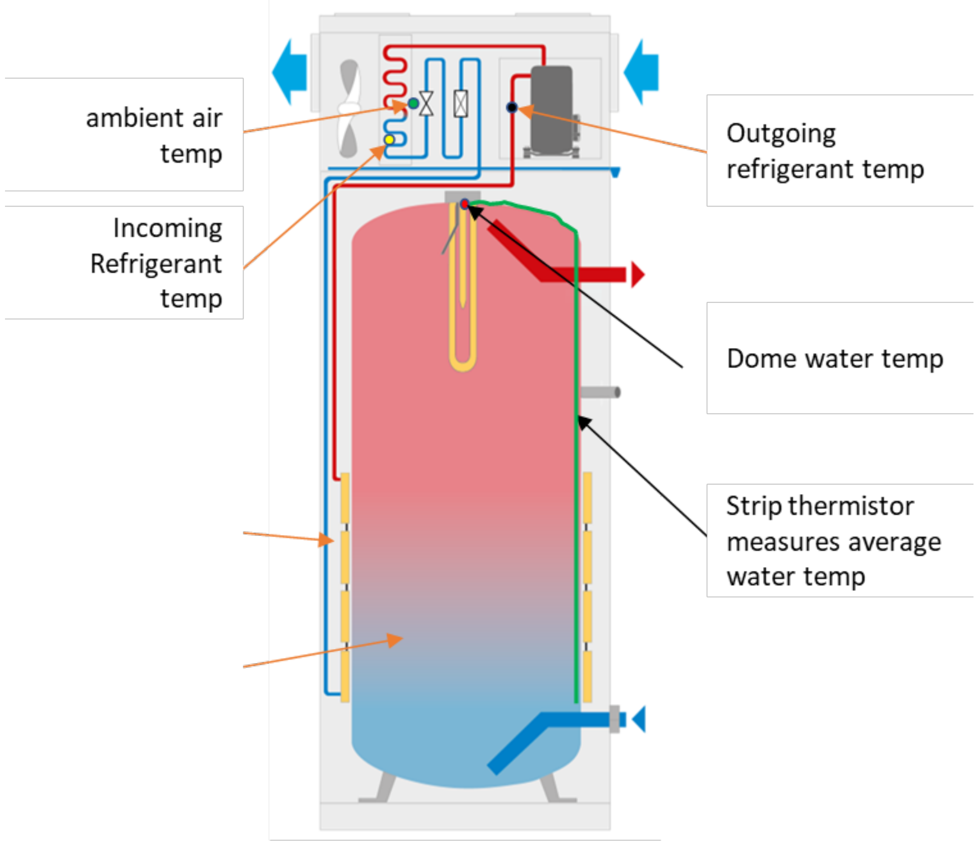
Data reporting rate:

1 minute (adjustable)

Data acquisition entities:

1*	1st setpoint temp	10	Error menu
2*	2nd setpoint temp	11	Hot gas switch temp
3*	Loading/heating level	12	Air inlet temp T1
4	Cylinder size	13	Hot gas temp T1
5	Mixed water volume	14	Evaporator temp T1
6	Electric element	15	Stored temp diff
7	Compressor	16	Dome temp
8	Fan	17	Integral temp
9	Defrosting		

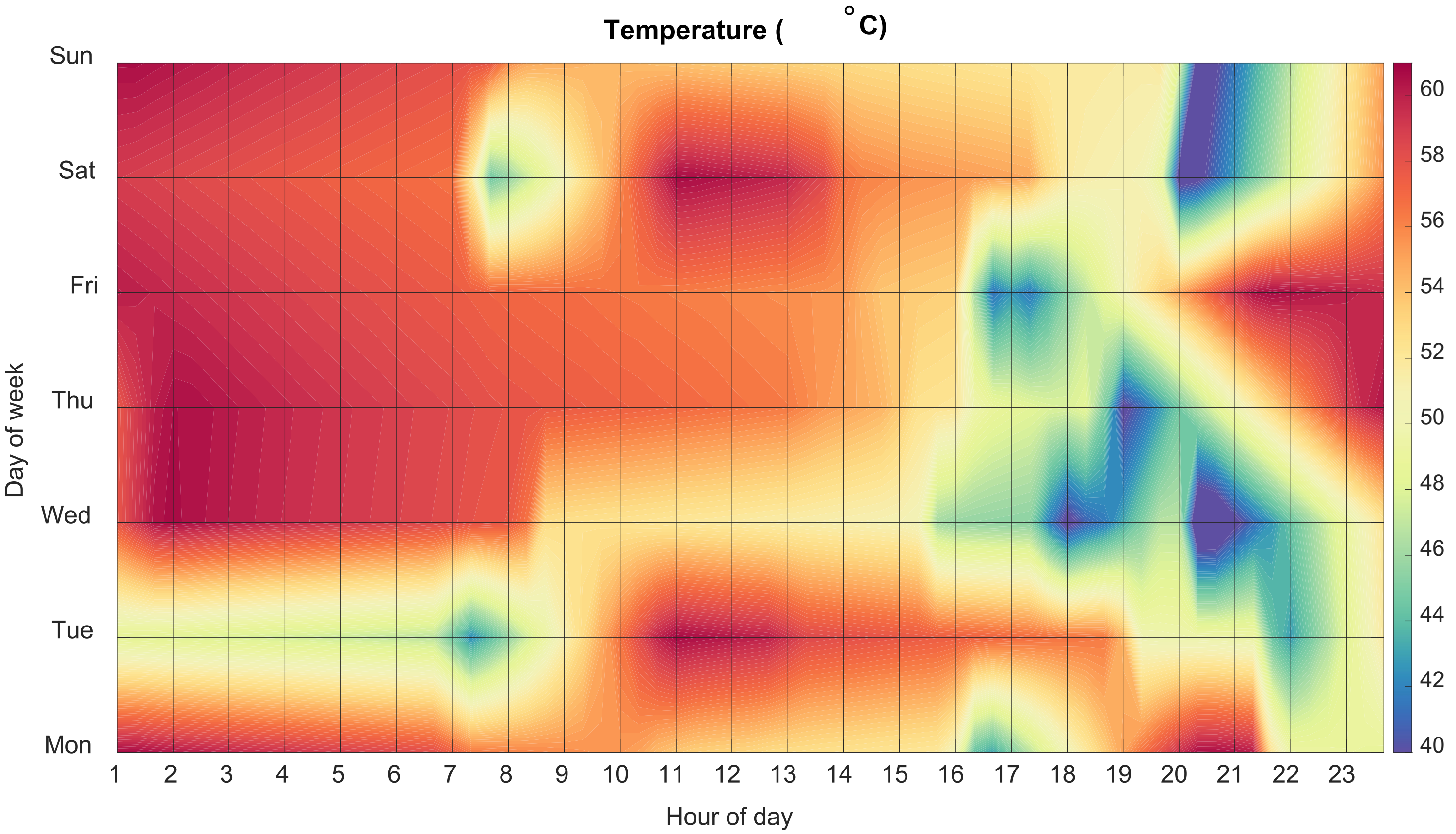
**1,2,3 entities are configurable*



- 1 installed at a family of 4 (in use)
- Test lab under construction that can mimic (different household behaviours and different environmental conditions)

Hot Water Usage Behavior Description

1. Understand customer usage patterns
2. Understand how HWS responds to those usage patterns
3. Identify opportunities for individually addressable
   - solar sponge
   - Demand Management



Load and Solar Forecasting

- Using weather variables as predictors
  - European Centre for Medium-range Weather Forecasting (ECMWF)
  - Bureau of Meteorology (BOM)
  - Global Forecasting System (GFS)
- Training on ECMWF data – “**Copernicus Climate Data Store”** data (hourly, worldwide – large data)
- Eight variables: Total precipitation, 2 m temperature, surface solar radiation downwards, surface thermal radiation downwards, U10 and V10 (10 m wind speed), total cloud cover, surface pressure
- Prediction of hourly aggregate load at various spatial aggregation levels; short term (e.g. hour ahead) to medium term (e.g. 46 day ahead forecast)
- Probabilistic rather than point forecast
- Originally aimed at battery scheduling for inverters – now for benefit of utilities

Weather data sources

- **European Centre for Medium Range Weather Forecasting (ECMWF)**

The extended-range forecast (HRES) provides an overview of the forecast for the coming 46 days, focusing mainly on the week-to-week changes in the weather. (e.g. windy.com) 0-1104 hours 6-hourly; 0-360 hours at 0.2 degrees; 360-1104 hours at 0.4 degrees. 50 ensemble forecasts.

- **Global Forecasting System (GFS)**

Public domain access – 0.25 degrees resolution, to 384 hours (16 days). (e.g. wxcharts.com)

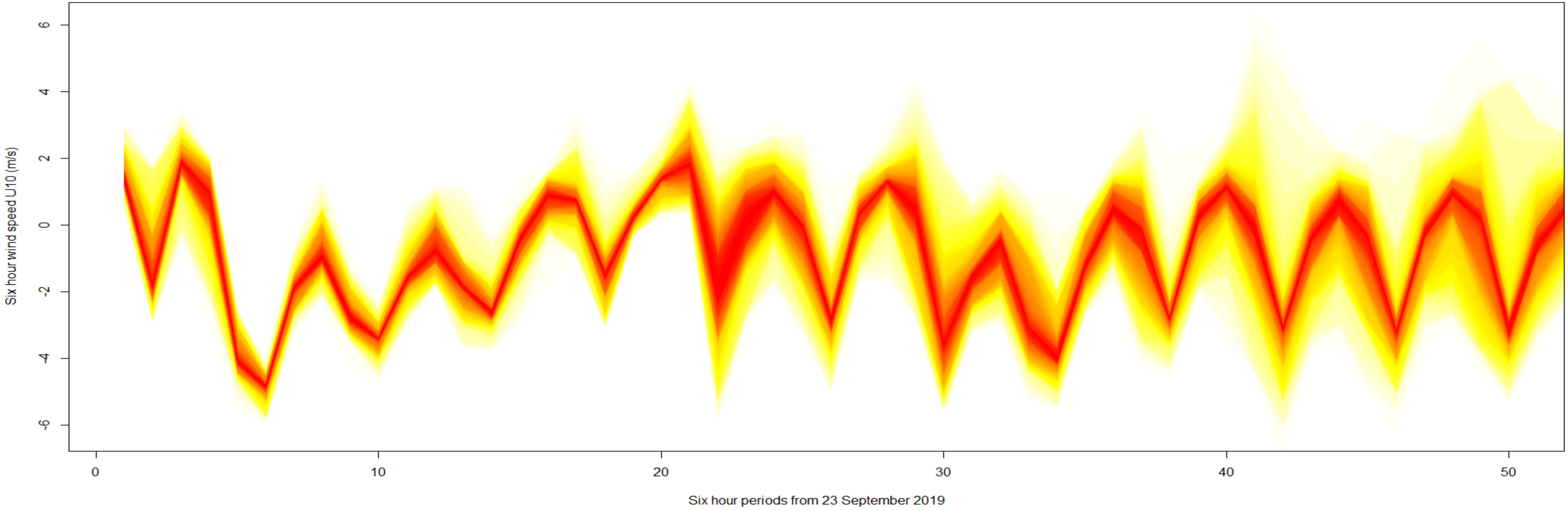
- **Bureau of Meteorology (BOM)**

APS3 ACCESS-C – 0.0135 degrees (~1.5 km) around cities; hourly to 36 hours

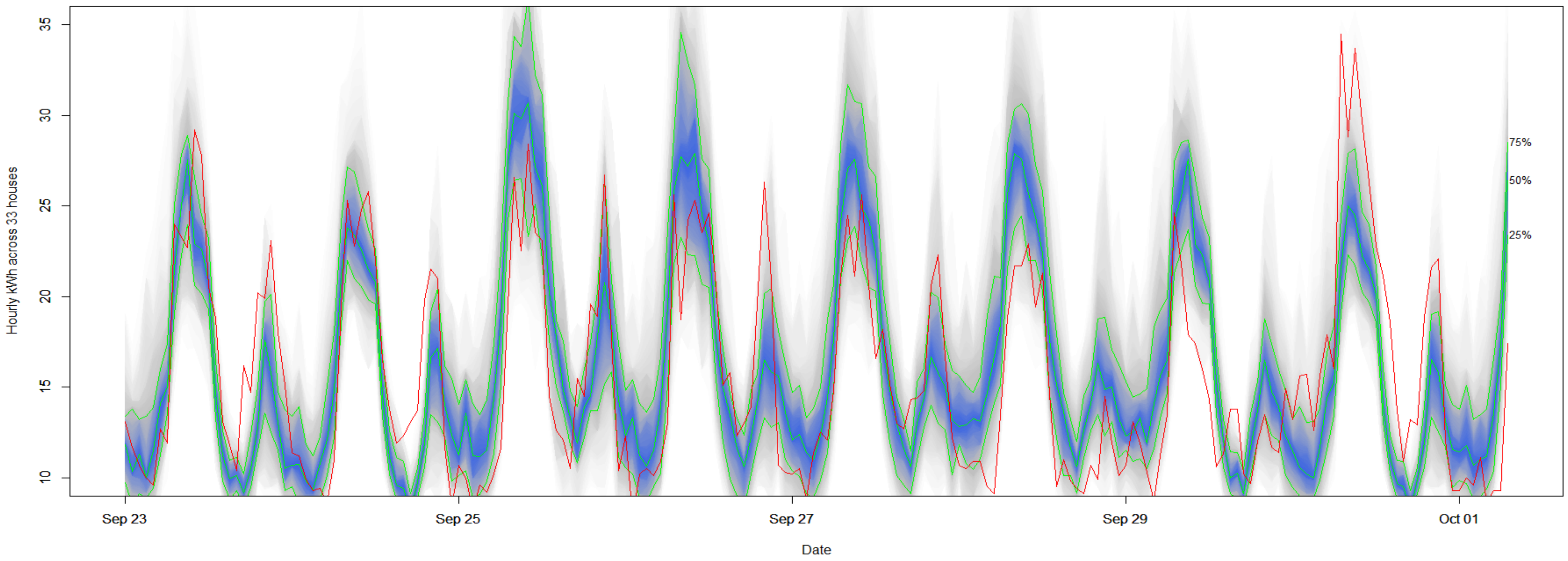
Business Demands for Numerical Weather Prediction

Sector	Sector Needs	Outcome	Output
Energy	"I need to know the amount of solar radiation reaching the ground, so that I can plan the productivity of major solar farms and make high value decisions and ensure that there is enough power available to meet demand. I need timescales of 3 hours to 3 days."	Information on solar radiation up to 3 days for specific locations	**City-scale model** APS: CE3 APS: CE4

Six hour wind speed U10 (m/s) zonal east-west



Probabilistic load forecasting – 33 houses



Further work/research

- Practical considerations – Python has better integration with Azure than R
- Legal considerations – anonymization and protection of data
- Data considerations – need more data; an accurate "ground truth" information for phase ID and a consistent source of data for aggregate load on a feeder
- State monitoring of networks
- Visualizations – e.g. different kinds of customer, projected to two dimensions
- Better understanding of metering and how it relates to billing (parallel with Metering and Settlement)
- Forecasting system interruptions due to severe weather conditions

A new lens for decision making

- True bottom up aggregation using actual data
- Higher precision forecasts and predictions that improve over time
- Accurate evidence based business cases
- More explicit performance measures

- Reshaping the internal decision making culture of networks

Other lessons

- Many use-cases – be clear on yours

- It’s not about the technology it’s about the data
  - Technology lasts five years
  - Low cost is best (cloud, IoT)
  - New generations mean better features
  - People might pay for better features
  - There may be multiple business cases for payback of data collection

The University of Queensland
Australia
CREATE CHANGE

Thank you

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