# AMIDiNe: Analytical Middleware for Informed Distribution Networks

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# Power Distribution in Transition

AMIDINe
Analytical Middleware for Informed Distribution Networks

- Last mile of power systems is the Distribution network:
  - Low Voltage (LV), originally intended to deliver power to end users. Nothing else.
  - Simple. No monitoring required.
- But now:
  - Low Carbon heat and transport result in higher loads on un-monitored networks
  - PV on LV networks not reported but can cause voltage issues – again, no monitoring to quantify impact
  - Transmission awareness of distribution behaviour lacking
- Do we need monitoring everywhere before we go any further with this?

# Ways to Understand…

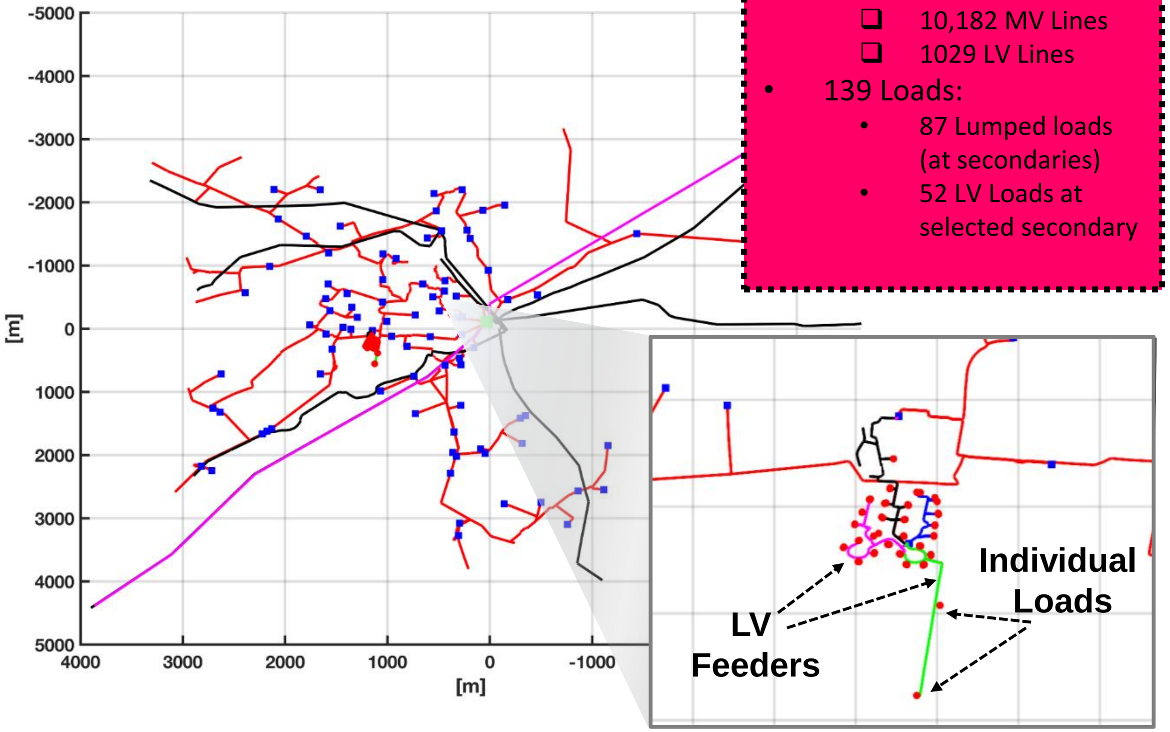
- Monitoring
  - Costs money
  - Where/when/how often?
  - Better with simulation?

- Do both…?

- Simulation
  - Are assumptions right/realistic?
  - Time resolution?
  - Better with monitoring?

- Do both…?

# Certainty and Uncertainty




- 11,299 Nodes:
  - 10,182 MV Lines
  - 1029 LV Lines
- 139 Loads:
  - 87 Lumped loads (at secondaries)
  - 52 LV Loads at selected secondary

- Know how the network fits together
- Well understood power systems models indicate how it will behave
- Key unknown is what the loads are and what they will do
  - LV distribution features little (no) monitoring
  - Not much forecasting done at LV – no need until now
- Can Machine Learning models capture the load unknowns, then use power system models to estimate the remaining network parameters?

# AMIDiNe

- 2 Year EPSRC funded programme of research
  - Development of tools for **managing demand uncertainties** faced by Distribution System Operators
  - Bringing together Machine Learning with Power Systems modelling
- Partners: Strathclyde (Lead), Oxford, Drax (Opus Energy), SSEN (GB DNO and TNO), Bellrock Technology, The Countinglab, PNDC + support from SERL
- **Started 1st October 2019 – now extended to September 30th 2022**
  - Additional industry funded projects pulling outputs through to higher TRL in parallel

# CONSEQUENCE OF LV BEHAVIOUR

# Modelling at LV

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- LV feeders number in the 10s of 1000s in most DNO license areas
- Although fairly simple (cables, CBs, transformers + some automation) can be variability in topology, spec and therefore behaviour
- Stringy rural feeder not like dense urban one
- Voltage and thermal constraint violations possible under some circumstances

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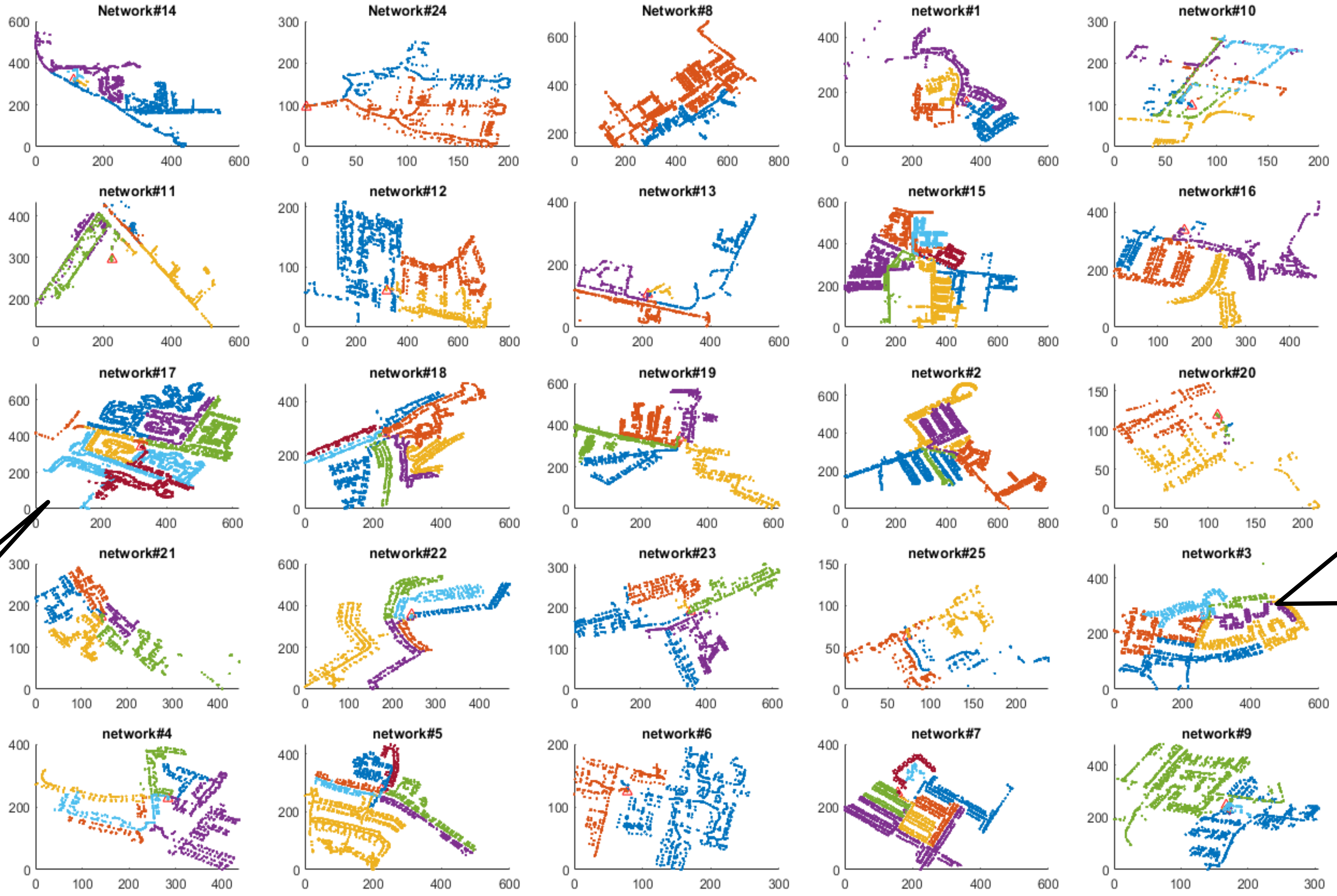
# LV Feeders below 11kV…



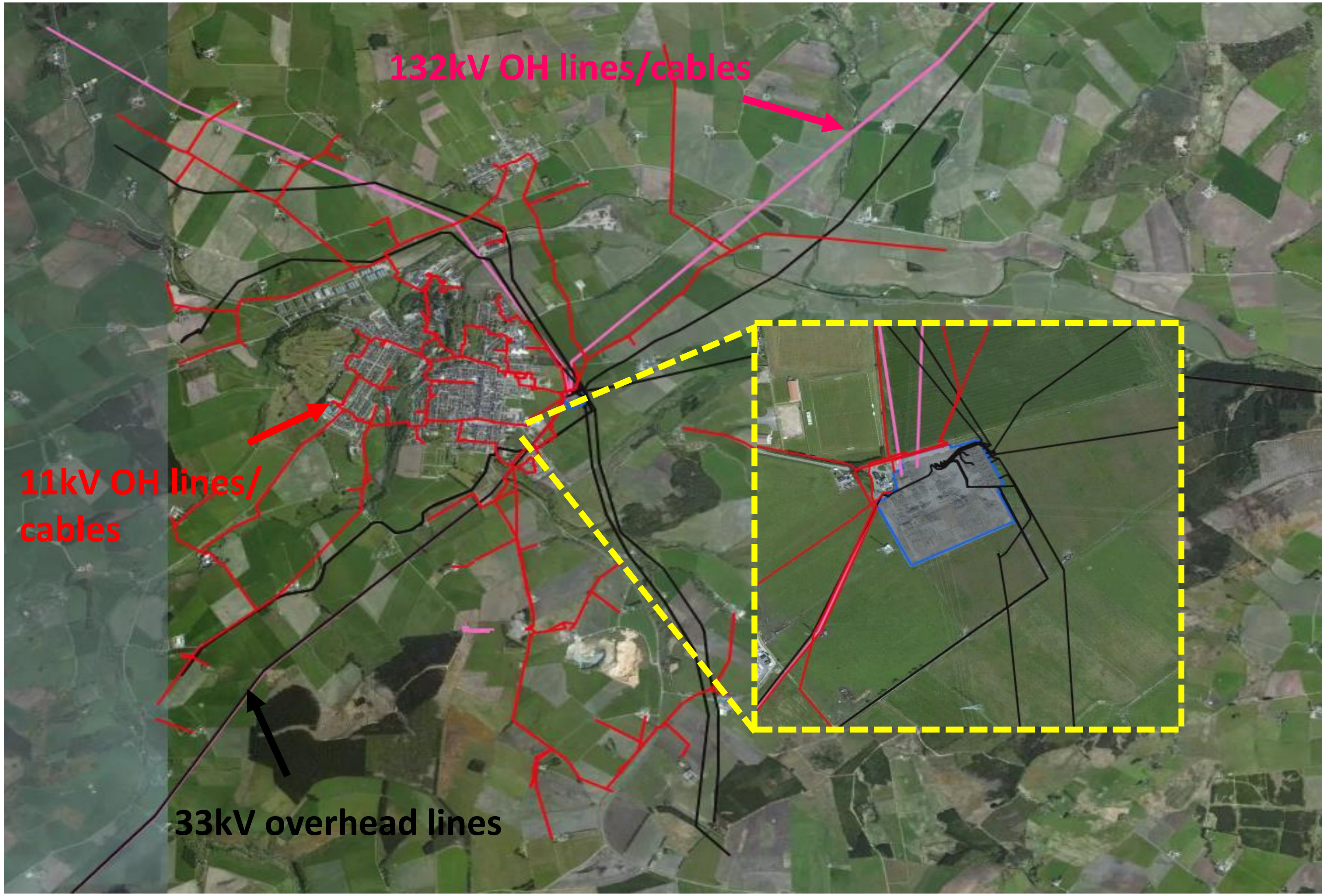

…125 LV feeders from a UK distribution network…

…all very different - bespoke modelling not scalable/practical

# AMIDiNe Solution

- Develop software that **automatically** converts raw GIS data into Power Systems (PS) Models, which are one-line representations of a particular network.
- Eliminate the need to manually translate from GIS data (**very time consuming/impractical**).
- Use open source software – no need for expensive licences for proprietary software e.g. ArcGIS.
- Population of PS models with metered substation (**or smart meter?**) load data.

# SHAPEFILES – GSP/PRIMARY

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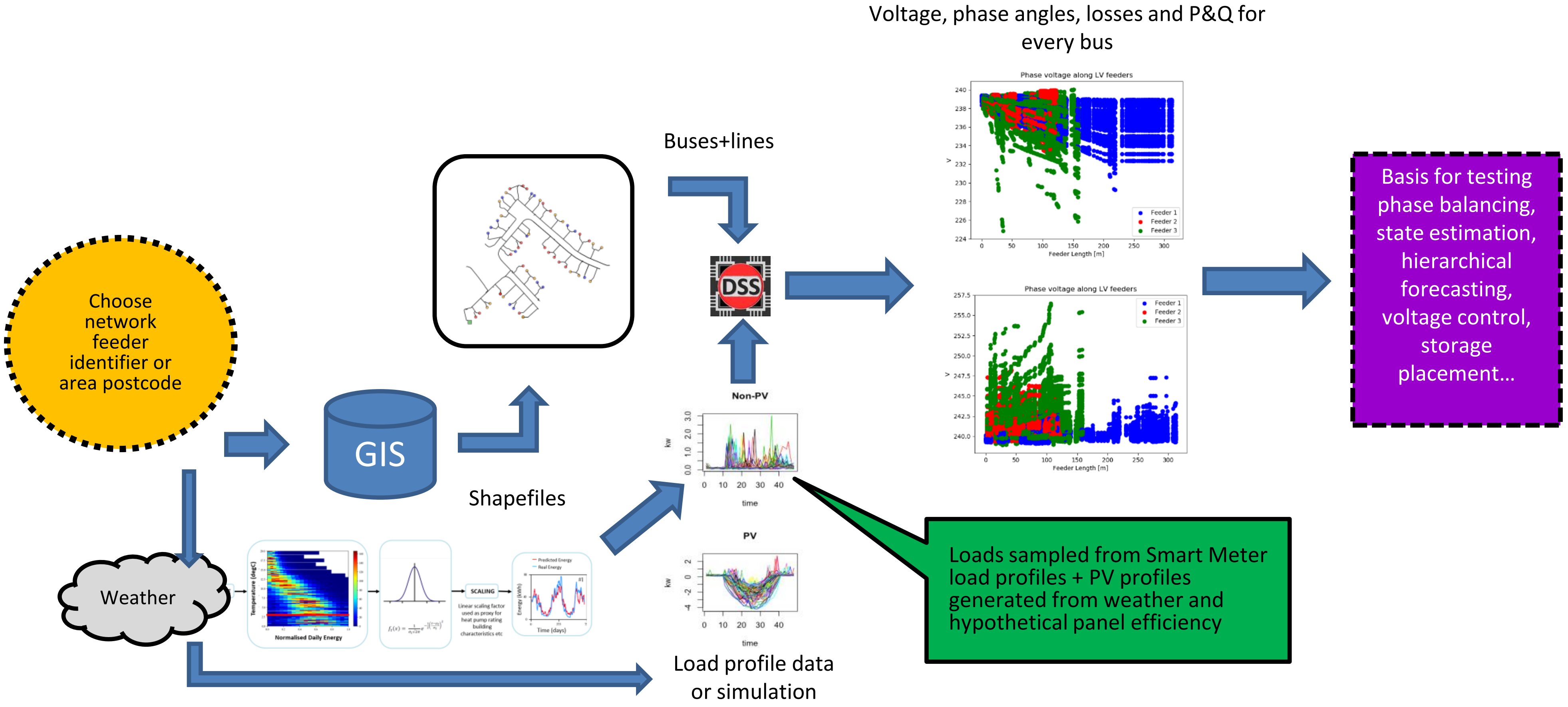
# Development Methodolgy



# EXAMPLES

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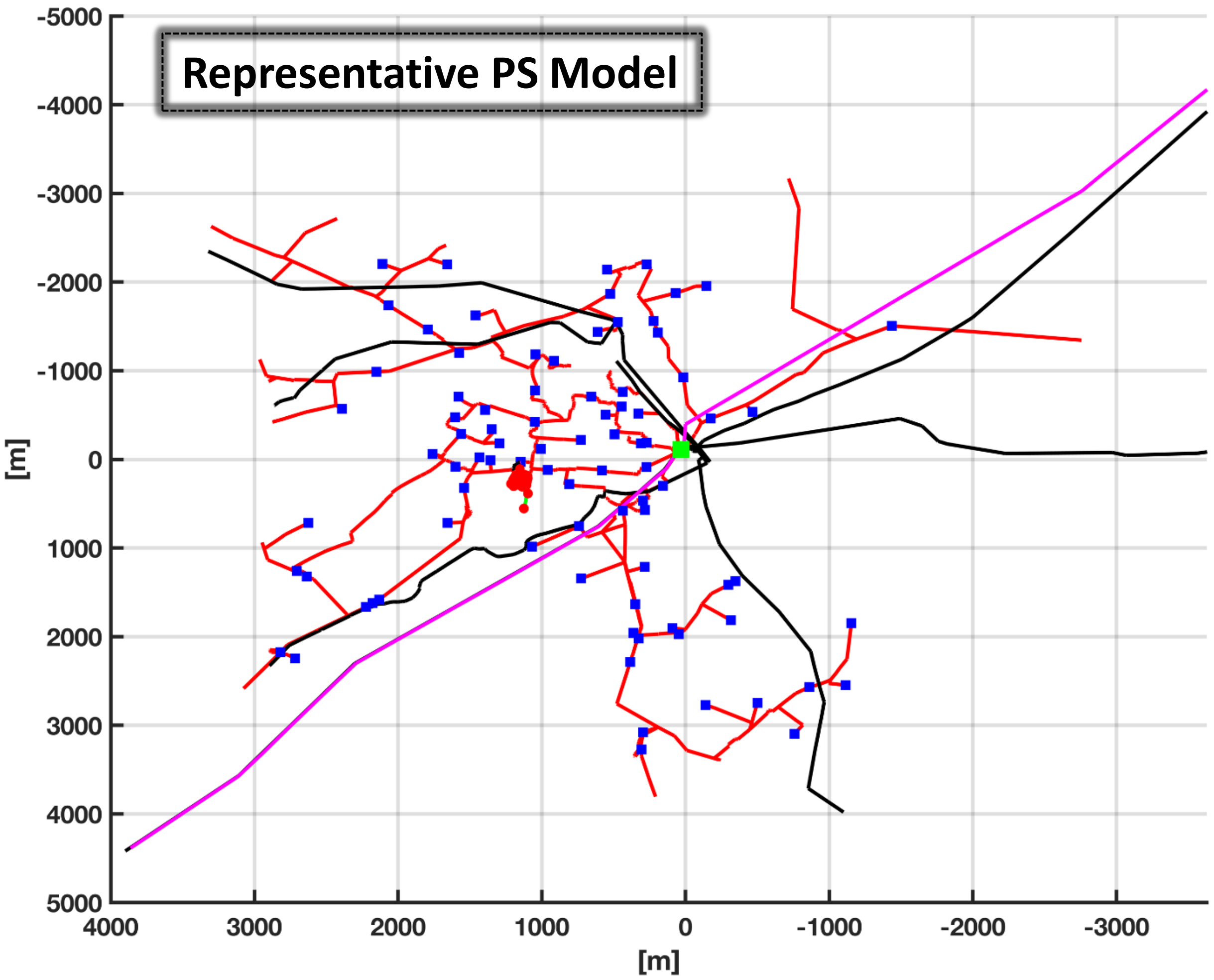
- Two application examples outlined here:
  1. Primary Substation model, **MV only** – Load at MV/LV secondary substations modelled as “Lump” Loads
  2. Primary Substation model**, MV and LV** – Detailed LV network modelling (hierarchy down to the premises) at select MV/LV secondary substations.

# PRIMARY SUBSTATION MODEL

## DETAILED LV MODELLING AT SELECTED SECONDARY/POLE-MOUNTED TRANSFORMERS

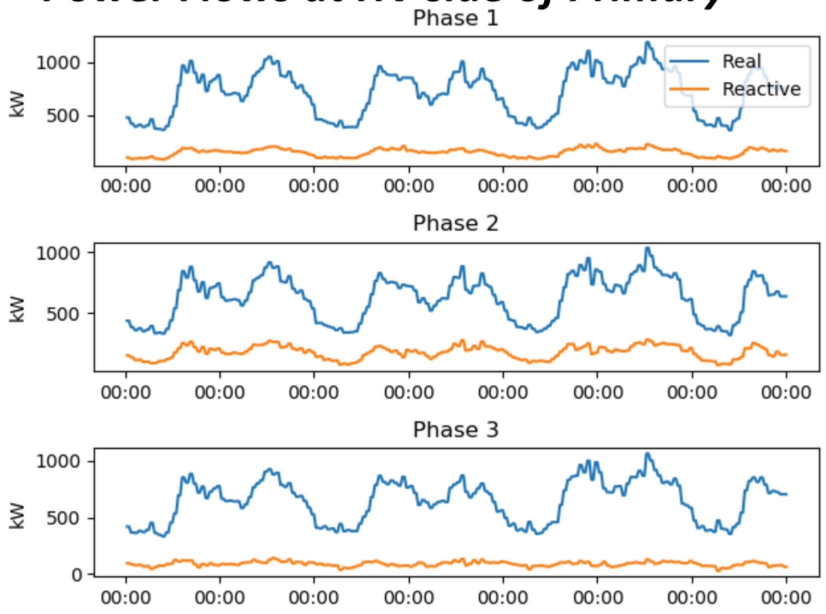



- 11,299 Nodes:
  - ❑ 10,182 MV Lines
  - ❑ 1029 LV Lines
  - ❑ 87 Lumped loads (at secondaries)

# PRIMARY SUBSTATION MODEL

## LUMPED LOADS AT SECONDARIES/PMs - SIMULATION

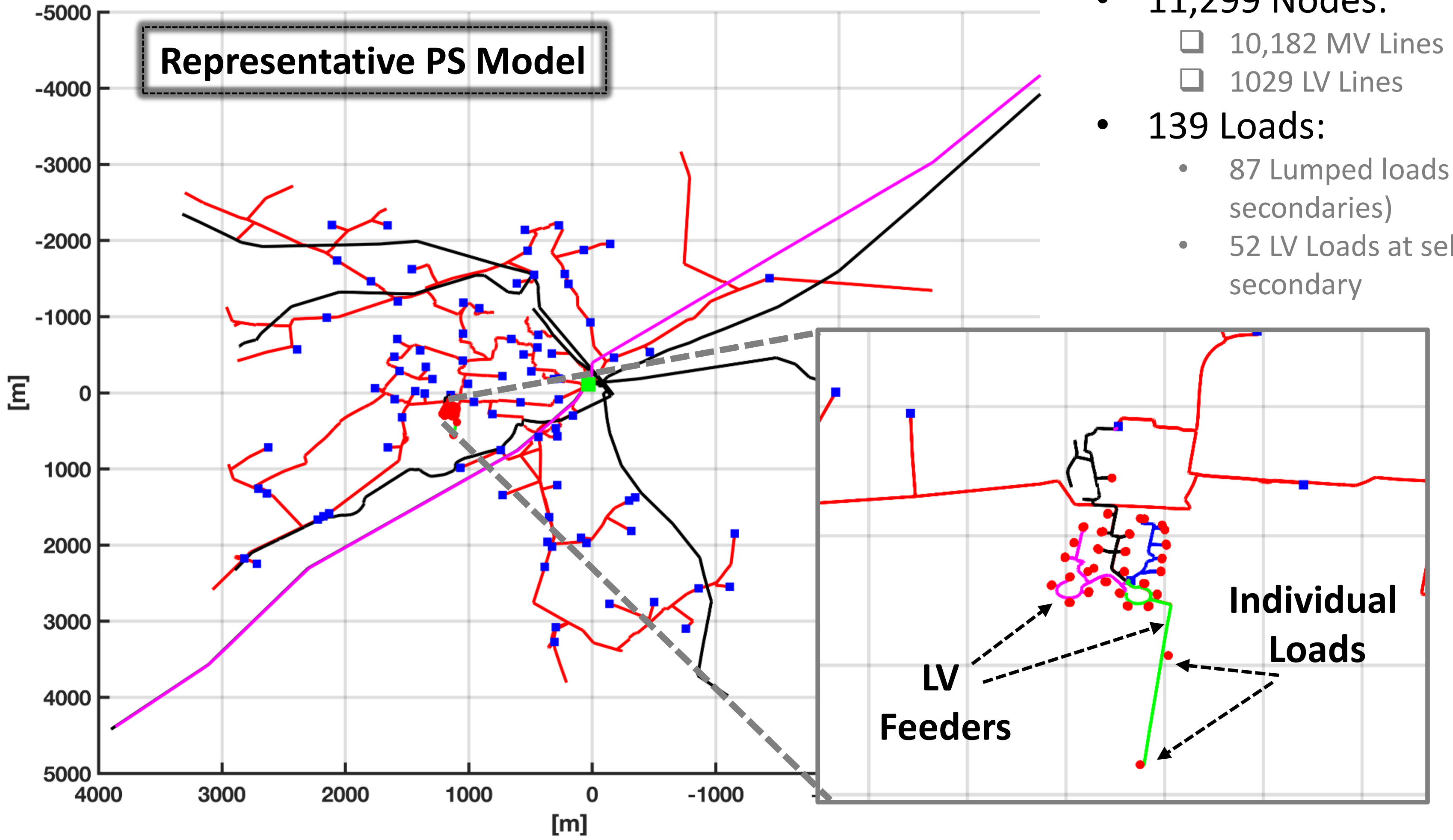
*Power Flows at HV side of Primary*




*Example of power flows at 38 Secondaries and 53 Pole Mounted Transformers*

# PRIMARY SUBSTATION MODELS

## DETAILED LV MODELLING AT SELECTED SECONDARY/POLE-MOUNTED TRANSFORMERS




- 11,299 Nodes:
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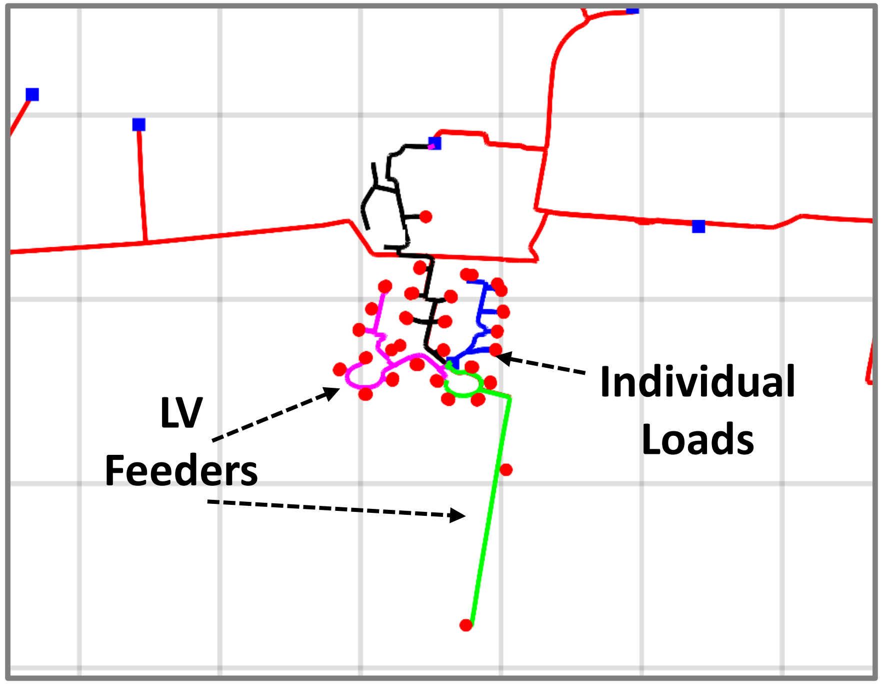
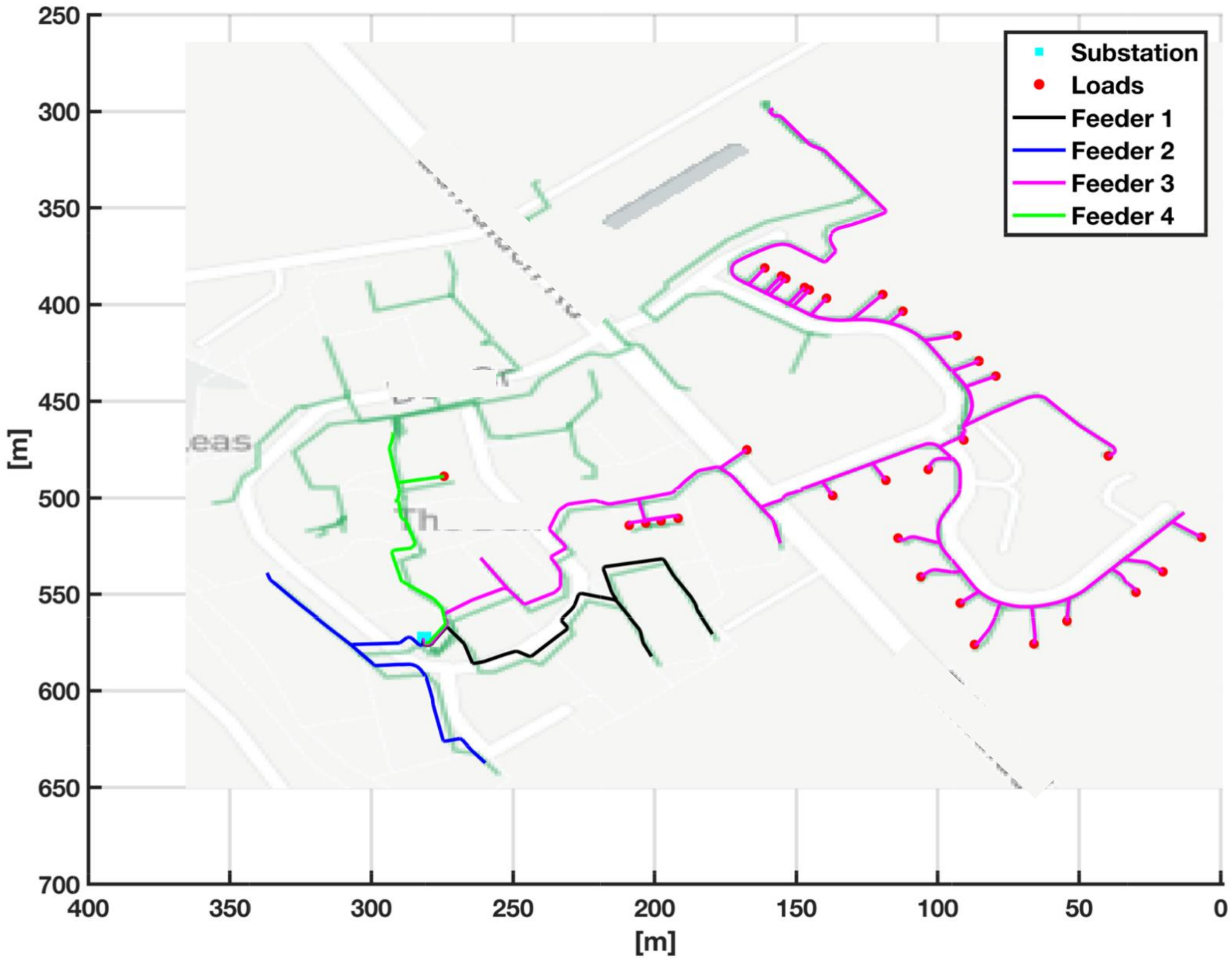
# Detailed LV Modelling at selected secondary/pole-mounted transformers




***Simulation Example***

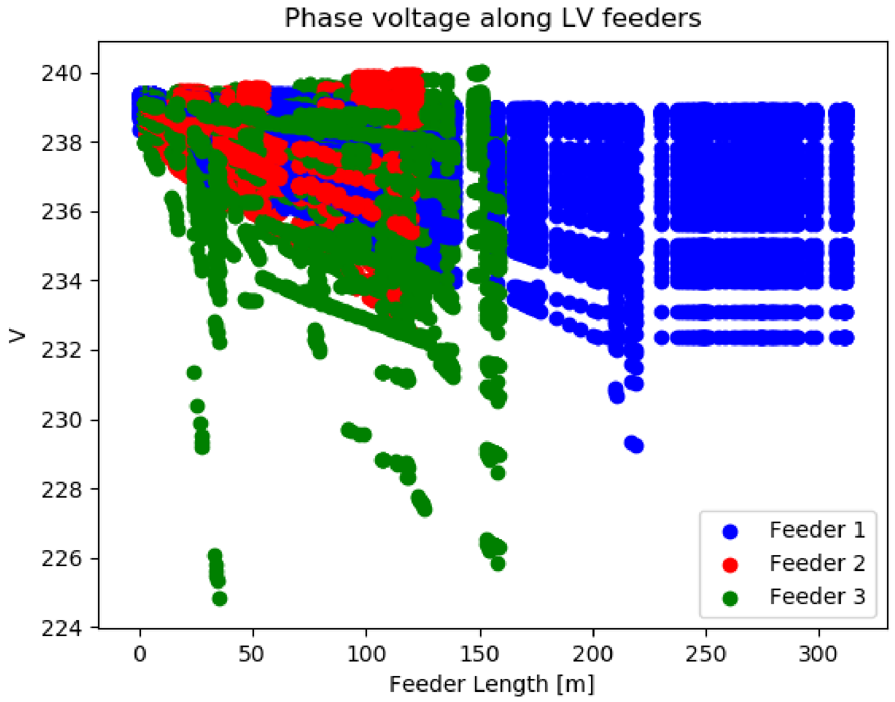
- Population of load data at 52 individual LV loads.
- Existing smart meter data used to model loads .
- Power flow simulated across 7 day period – results extracted and analyzed.



Substation
Loads
Feeder 1
Feeder 2
Feeder 3
Feeder 4
250
300
350
400
450
500
550
600
650
700
400
350
300
250
200
150
100
50
0
[m]
[m]

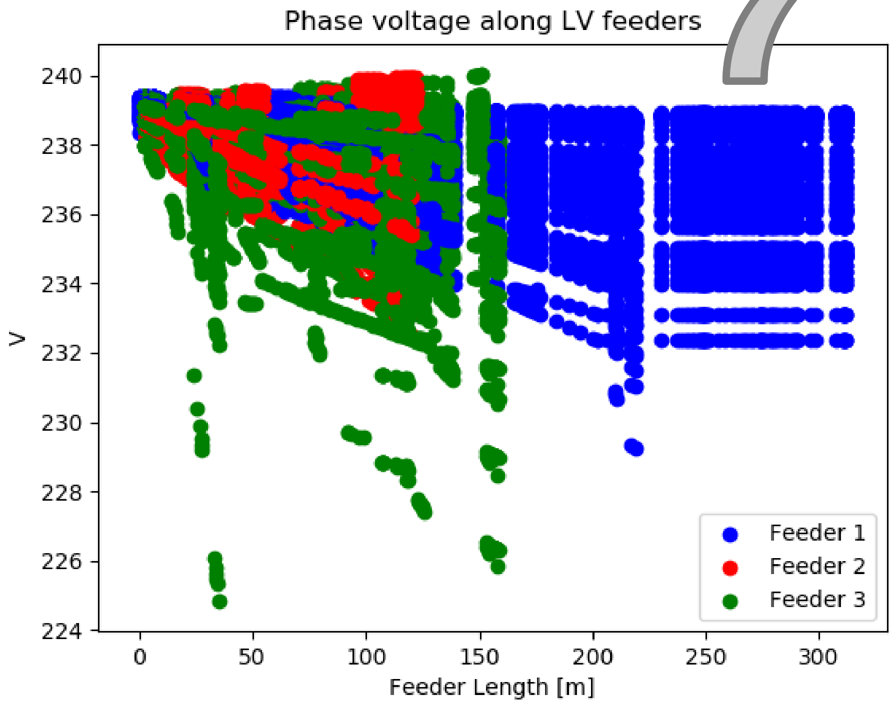
# Detailed LV Modelling at selected secondary/pole-mounted transformers

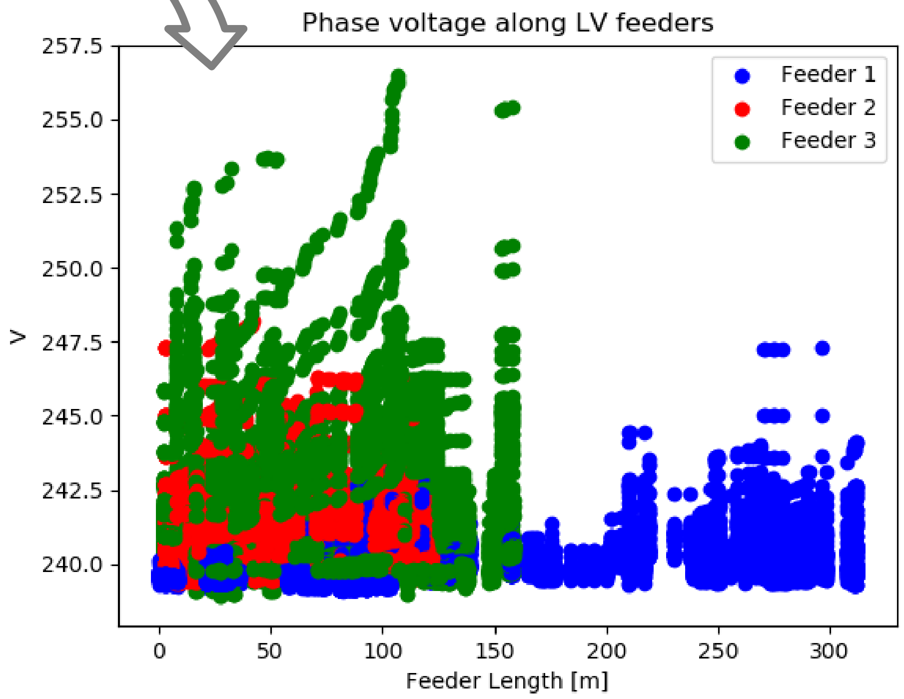
***Analyze LV phase voltages***



# Detailed LV Modelling at selected secondary/pole-mounted transformers

***Assess impact of embedded generation***



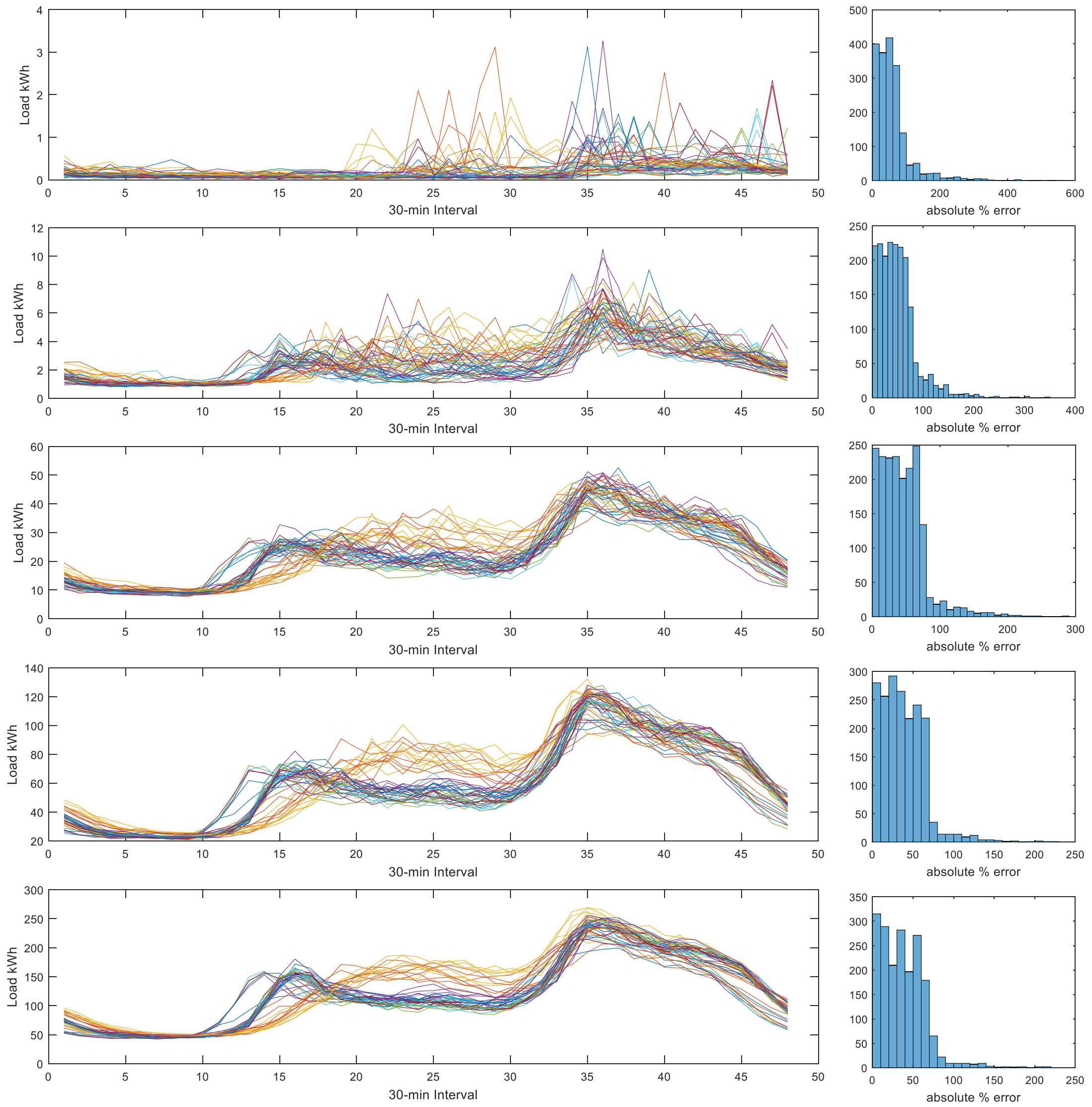
# FORECASTS FOR LV LOAD BEHAVIOUR

# LV Forecast Objectives

- In residential load forecasting the **low signal to noise ratio** makes skilful forecasting challenging, when compared to models for higher voltage levels
- Typical average error metrics, e.g. MAE/RMSE, in practice reward smooth forecasts --> **heavy penalisation of phase errors**
- However, **often peak demand at individual level** is important for dynamic pricing, battery scheduling, EV charging, etc.
  - Can we shift focus of the forecasting model to ‘cardinal point’ type models
  - For now let’s generate probabilistic forecast of daily peak demand intensity and timing
  - Can we do this hierarchically to the primary substation level?

## Daily Load Profiles

## % Forecast Error for Persistence




5 MPAN (>500%)

10 MPAN (>300%)

100 MPAN (>200%)

250 MPAN (>150%)

500 MPAN (100-150%)

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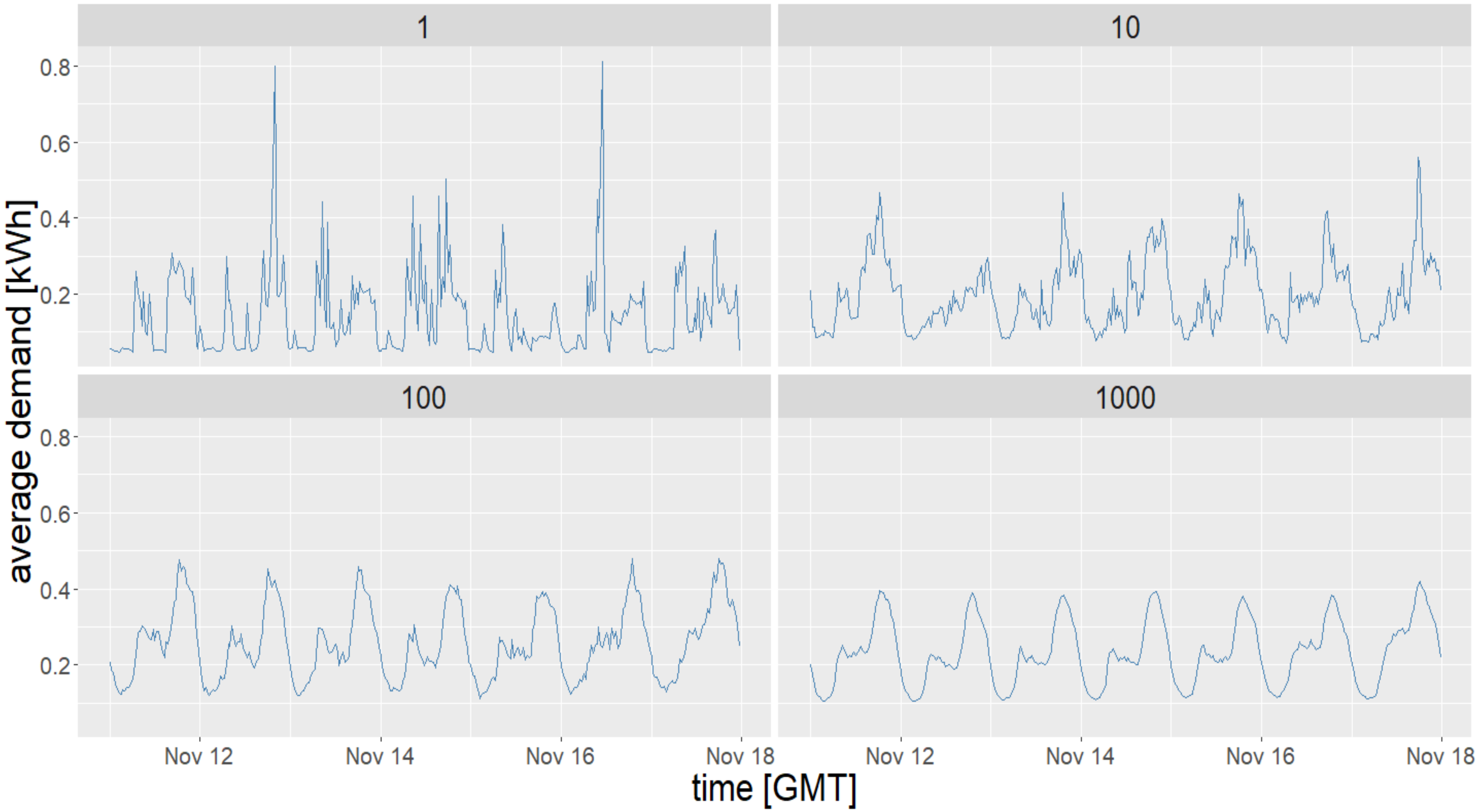
# Disaggregate demand

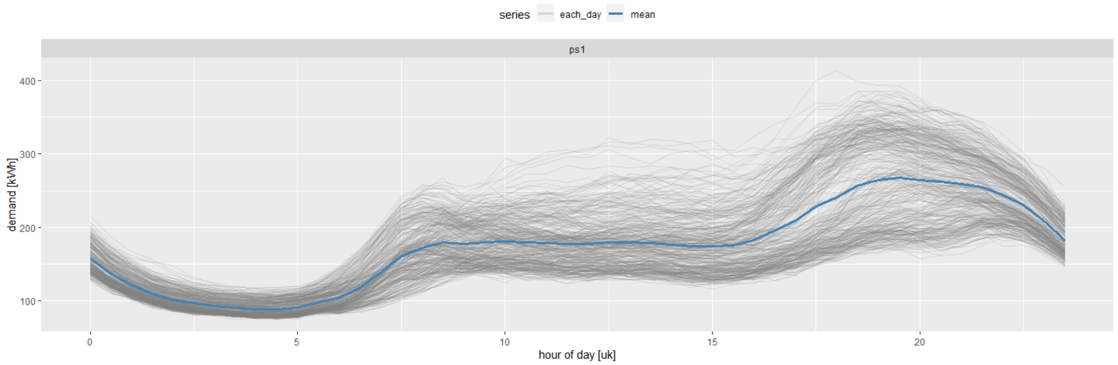
signal-to-noise ratio low at small aggregations




http://doi.org/10.5255/UKDA-SN-7857-2

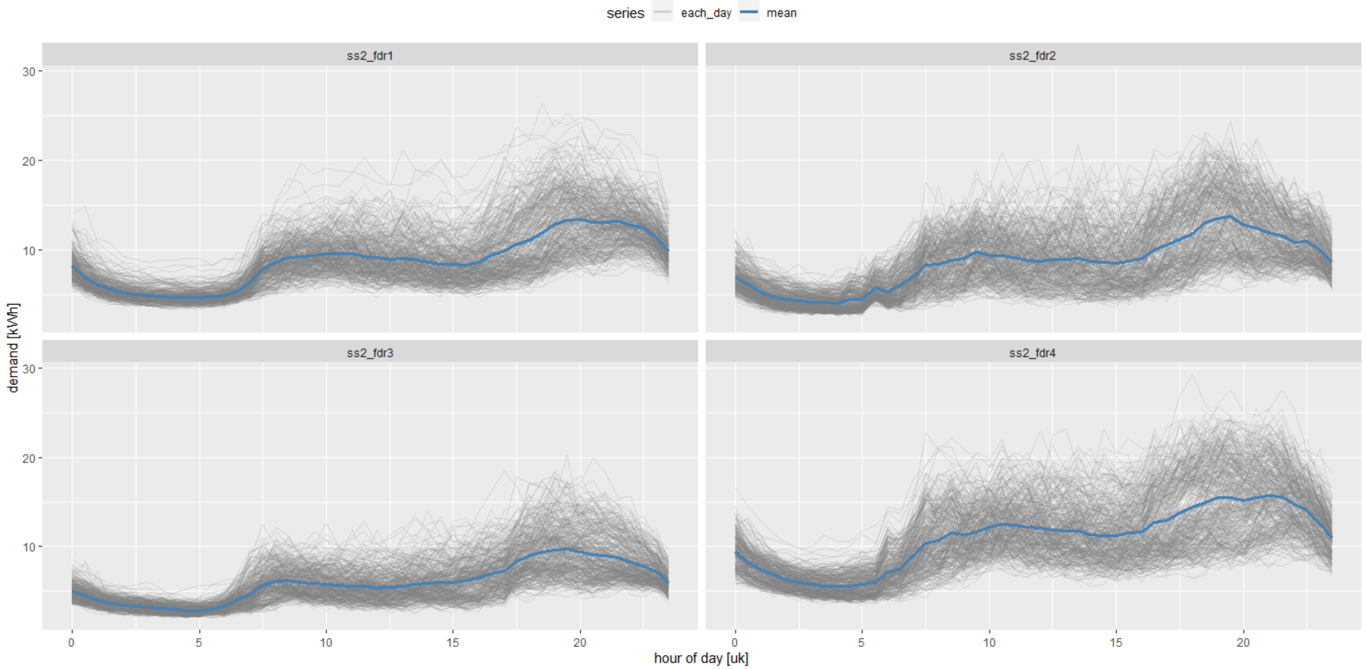
# Hypothetical Hierarchies

## Daily profiles - aggregate levels



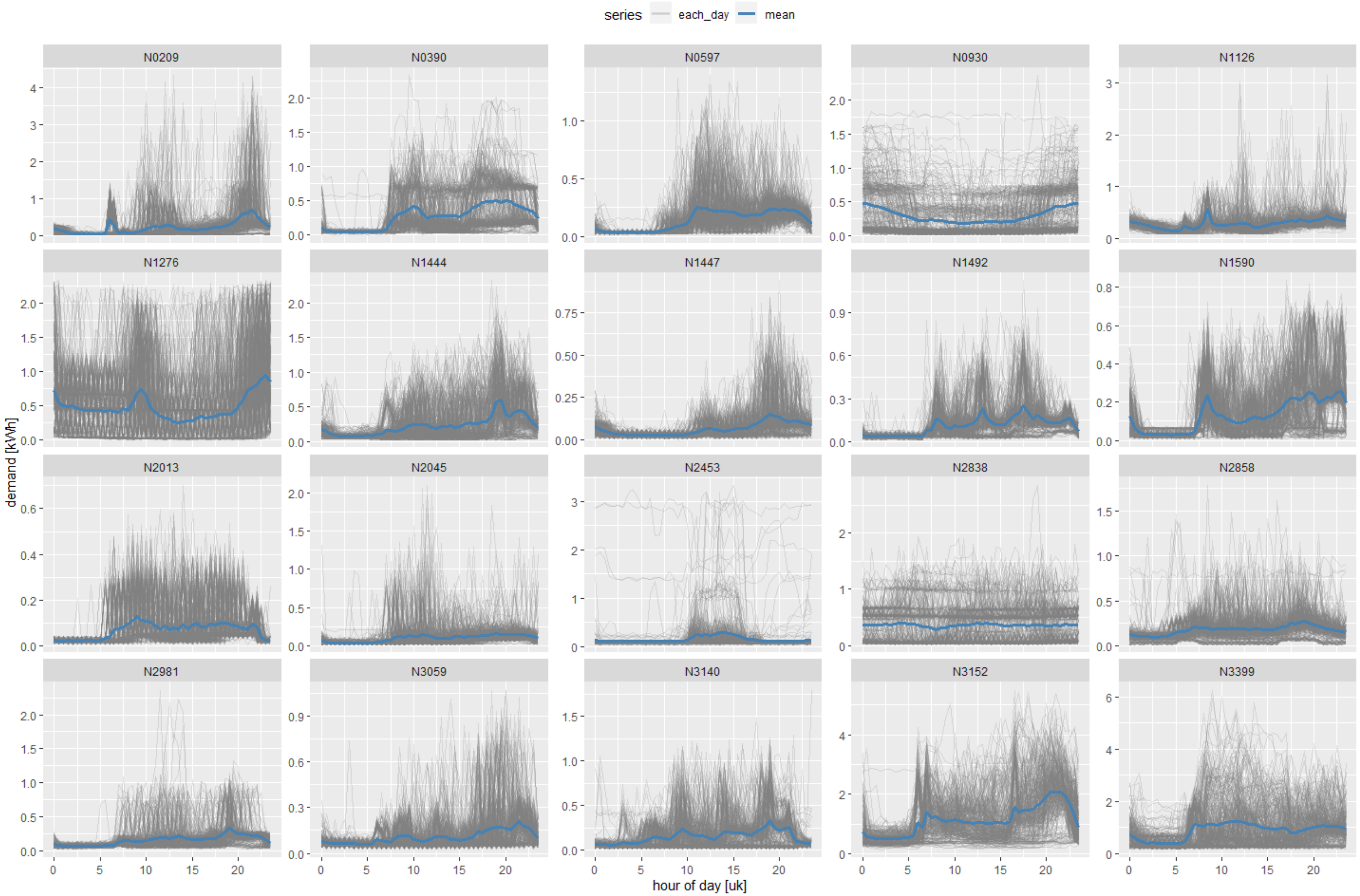

Primary Substation

Feeders



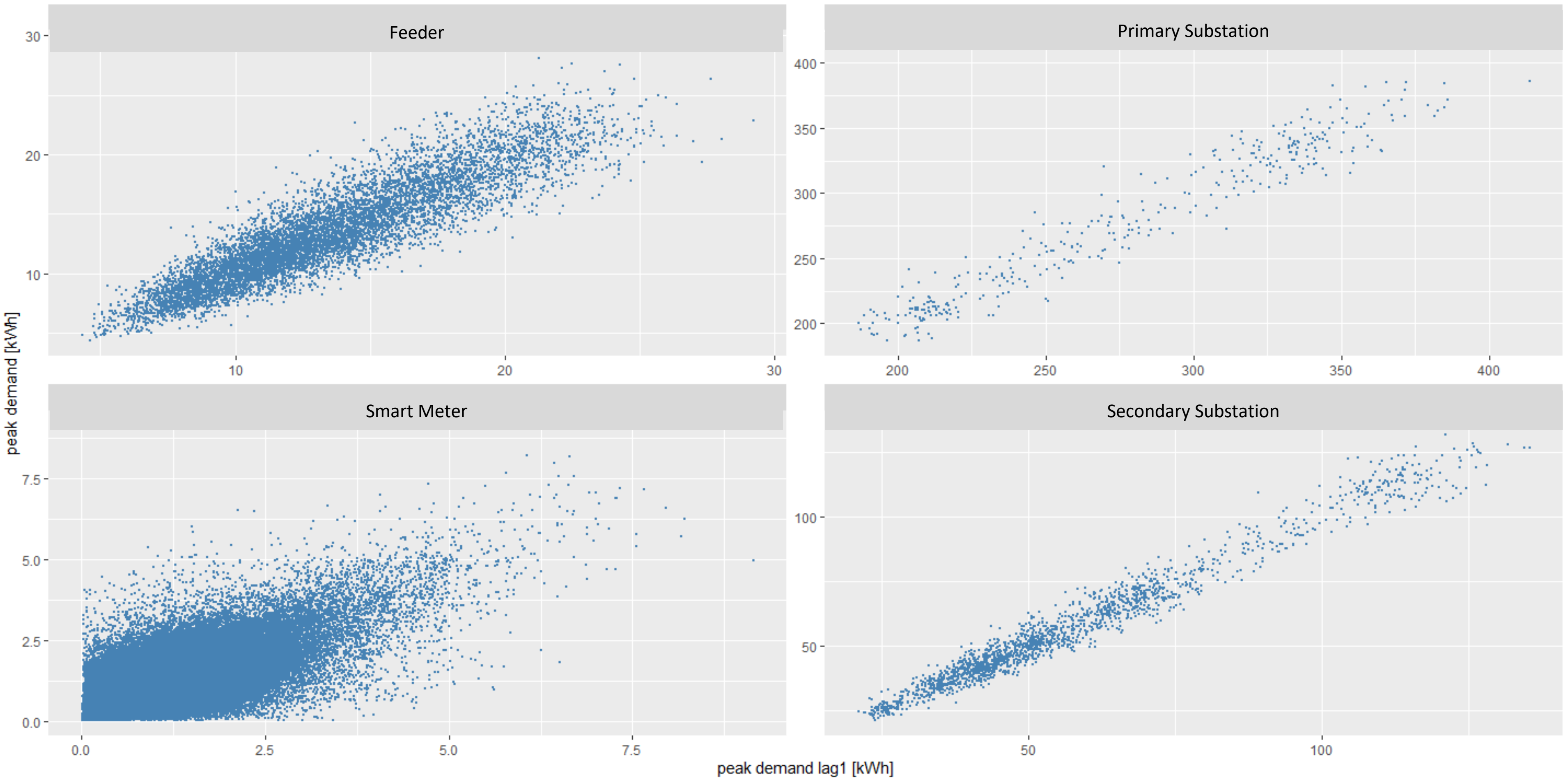
# Hypothetical Hierarchies

## Daily profiles – smart meters



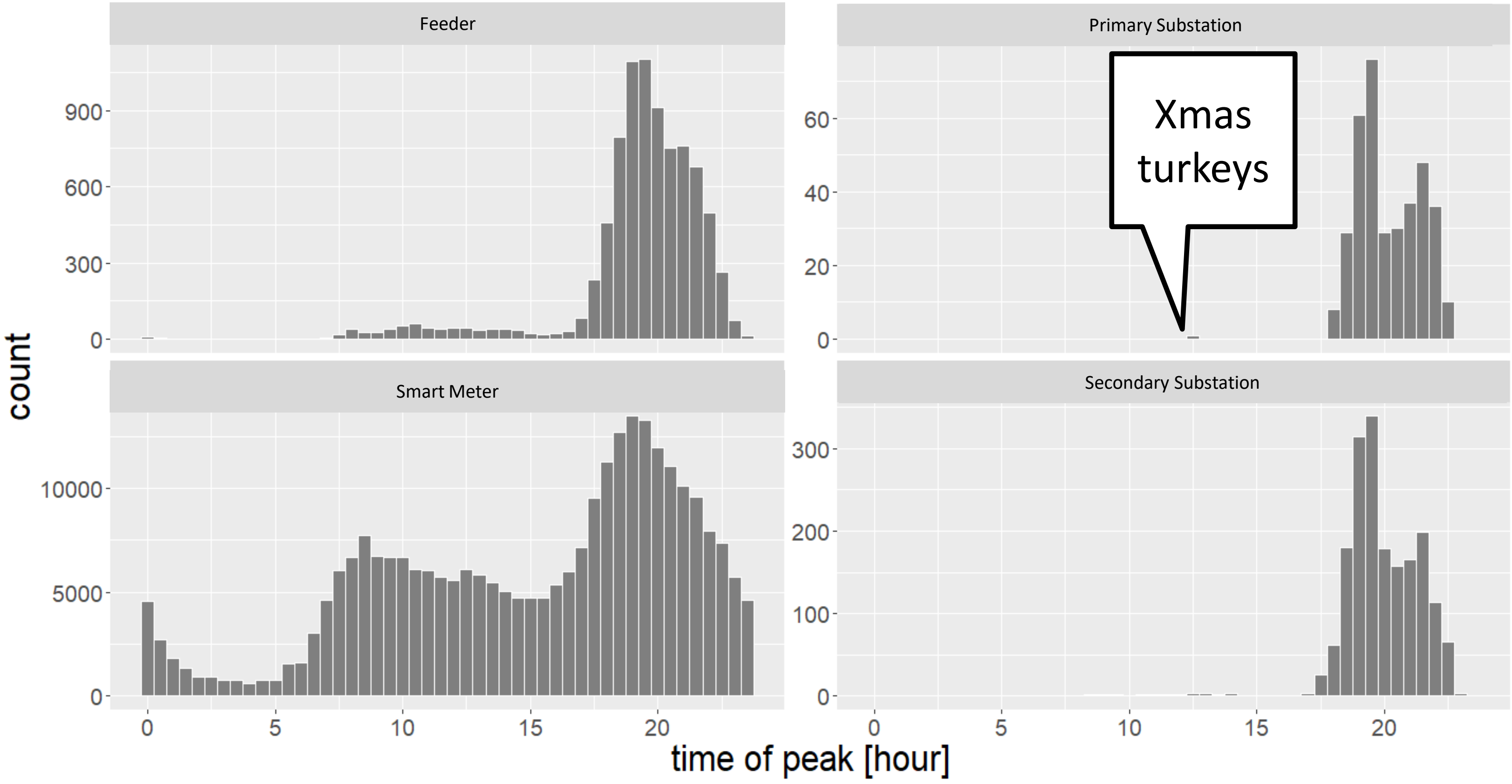
# Daily Peak Demand

## Lag-dependency

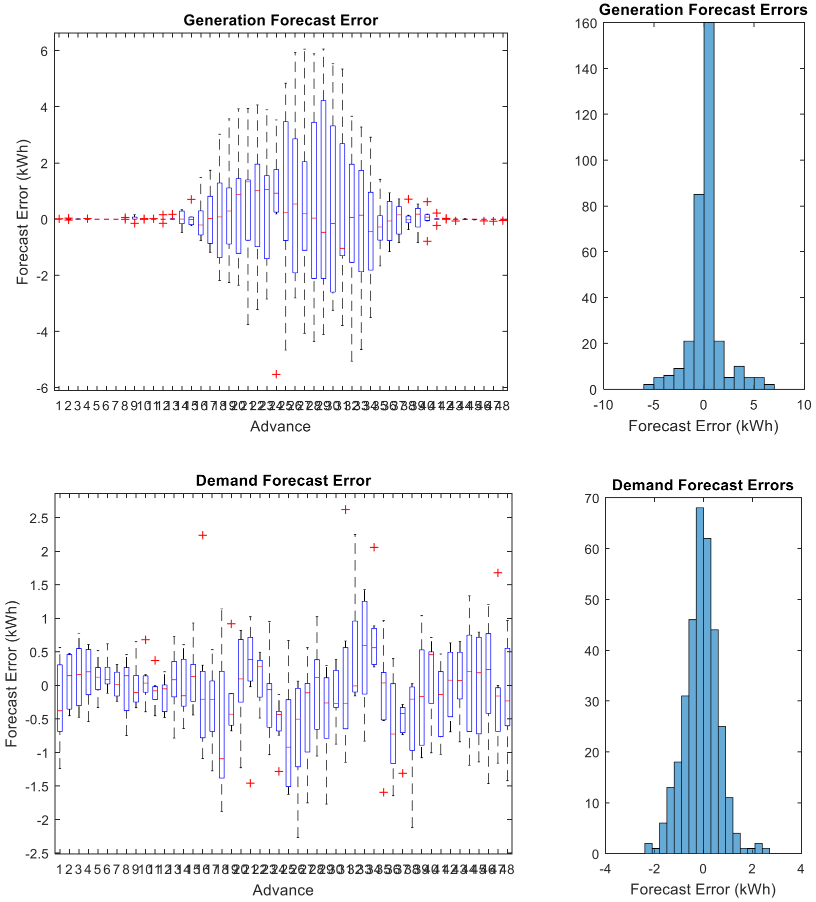


# Daily peak demand

## time of peak



# Measurement of Forecast Utility…

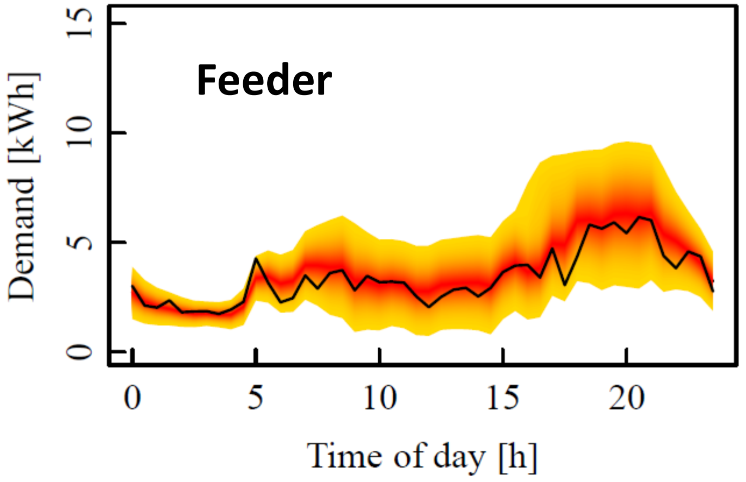


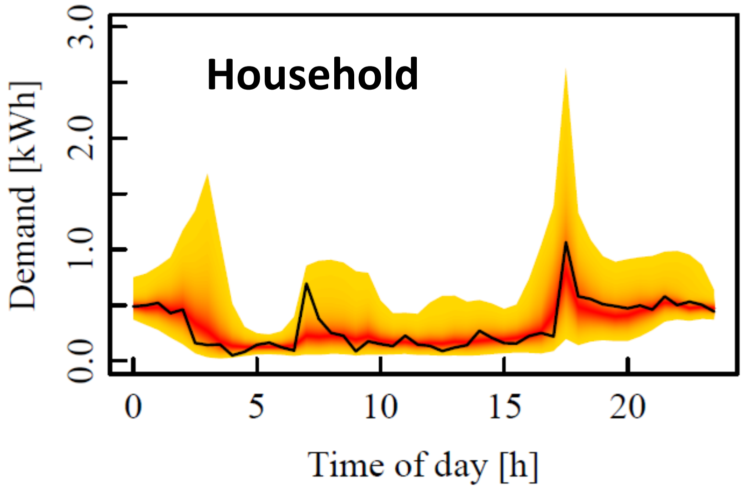

| Forecasting model | Forecasting abs % error | Performance of scheduler model | |
|---|---|---|---|
| | MAPE | Grid export reduction (reduce surplus at trough) | Self-consumption increase (reduce deficit at peak) |
| | [%] | [%] | [%] |
| Ensemble forecast (all) | **27.4** | 80 | 75.6 |
| Gradient boost machine | 29 | 79.1 | **78.3** |
| Persistence forecast | 29.7 | **82.3** | 73.2 |
| Gaussian process | 30.6 | 80.3 | 76.5 |
| ARIMA model | 48.2 | 74.9 | 74.6 |
| FF Neural network | 50 | 71.4 | 70 |

# Forecasting for Distribution at LV

- Need general-purpose forecasts that capture peaks
- Fusion of conventional and a bespoke “peak” forecast
- Peak forecast: bivariate prediction of size and timing of peak
  - “Time of peak” as hazard function

- Generalised Additive Models for Location Scale and Shape used extensively
  - Additive models for each distribution parameter
  - Generalised Beta Prime

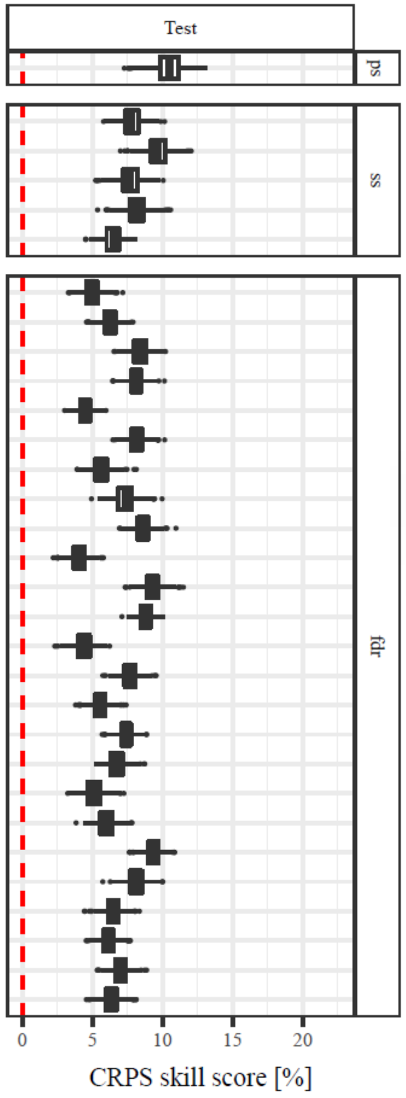


# Forecasting for Distribution at LV

- Performance gain vs state-of-the-art conventional forecasts:
  - Primary to Feeder
    - Overall: 5-10%
    - During peaks: 10-20%!
  - Household
    - Overall: <1%
    - During peaks: 5%!

- A lot of gain for a little computation!




Details in forthcoming article with code and example data

Pull through to higher TRL/operational deployment

# TRANSLATION

# Translation Activities/Projects

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- Control Room Future
  - Ofgem Network Innovation Allowance (NIA) with UKPN and SSEN
  - Requirements gathering for DSO control room with greater degrees of automation
- Future Control Room Analytics
  - PNDC core research with SSEN, SPEN and UKPN
  - Bellrock Lumen deployment of forecasting and power system modelling tools
- Development of a State-of-the-Art Digital Twin for Enhancing Distribution Network Visibility and Unlocking Distributed Energy Resource Potential
  - Strategic Innovation Fund (SIF) with ScottishPower
- WPD Presumed Open Data (POD) Challenge
  - PSS demand and PV generation forecasting
  - ‘AMIDiNe North’ came in 12th

# Future Control Room Analytics: Objective and Motives

- DSO control room needs additional functionality from current implementation
- Distribution network actor behaviours are different from larger system players
- Required analytics either bespoke or just not available off the shelf – how to build capability in preparation for changes in practice/new practices?:
  - Identify analytics integral to DSO function
  - Implement these using the Bellrock Lumen platform as the data pipeline and use publicly available data to illustrate
  - Deploy on a platform which could allow all potential end users to evaluate it
    - Can’t second guess end users – need direct feedback

# 3 DSO Analytics

PNDC
UNIVERSITY of STRATHCLYDE

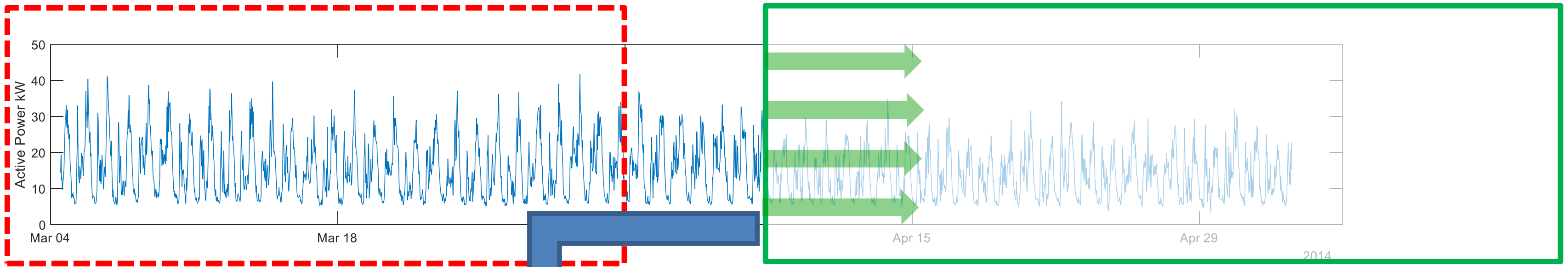
- 3 chosen by kick-off workshop participants were:

  1. Flexibility service provision tracker (how much flexibility, when)
  2. Hierarchical load forecast (where is flexibility) – Using a set of LV metering points from 415V up to primary, forecast load both at the aggregated and disaggregated levels. Hierarchical load forecast learns a *coherence matrix* which identifies the expected way forecasts fit together and corrects base forecasts before they are aggregated to a higher point in the network. Key learning: identifying where and when do base forecasts change behaviour.
  3. LV feeder digital twin (operational consequence)

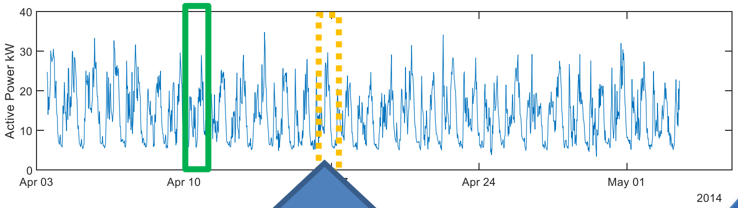
- 1 & 3 written in Python with a Django web based user interface; 2 written in R – key challenge here is integration with existing or heterogeneous workflows

# Analytic #1: Quantifying Flexibility

Forecast week ahead




Short Term Load Forecast Model



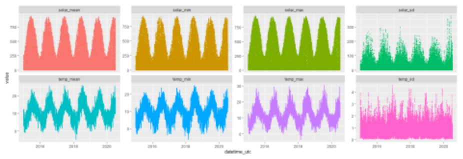

48 loads forecast for week ahead

1 month of 48 half hour load data – forecast 1 day ahead from 00:00

# Demand Model Training

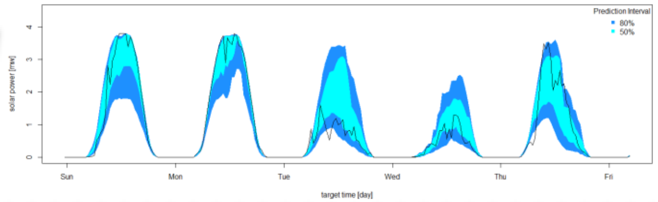
# Week Ahead Forecasting

# PV Generation Forecast

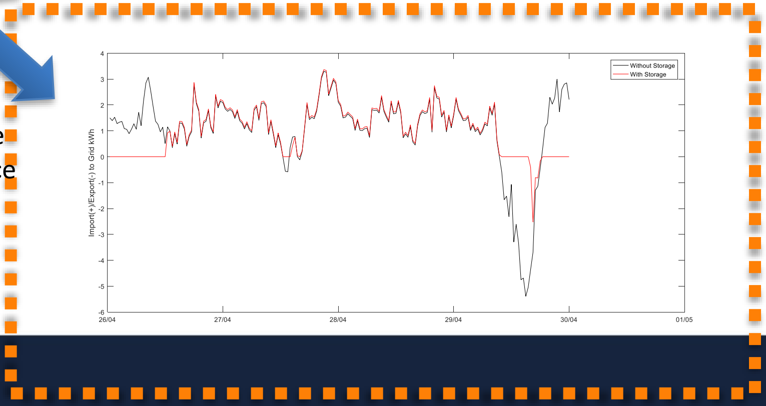


48 30 min avg. forecasts for week ahead

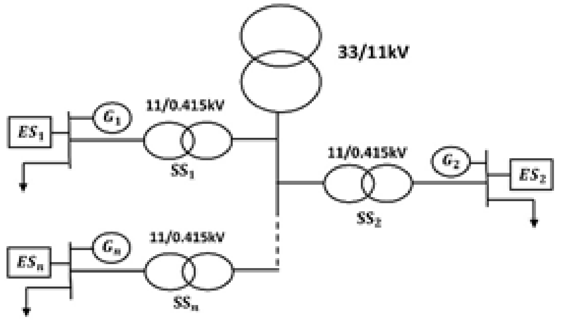
QR model learned on historical observations + NWP

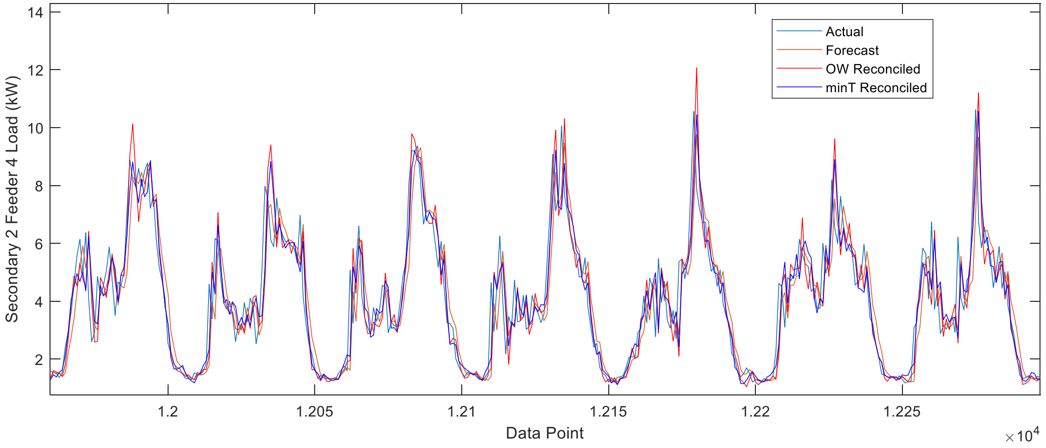


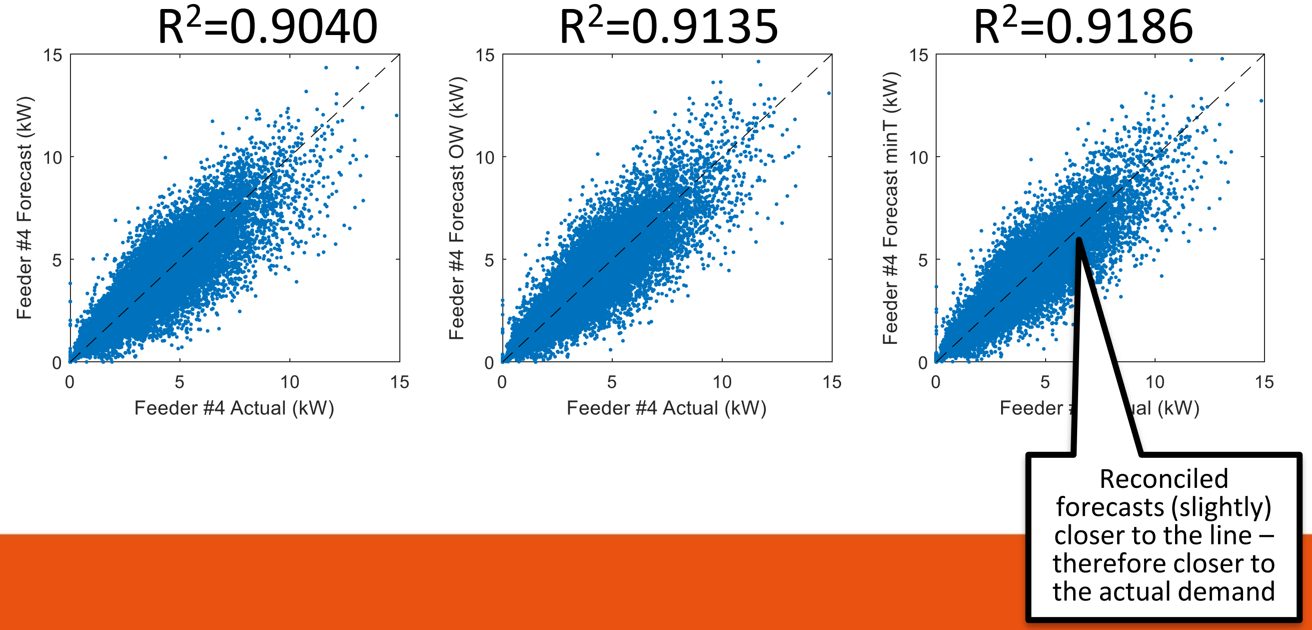

Anticipate Charge schedule and hence potential for flexibility…



# Analytic #2: Hierarchical Load Forecasting




**Data used – synthesised hierarchy**

- 1 primary substation
- 6 secondary substations
- 36 LV feeders comprising 40+ smart metered premises
- Needs to be bigger to be realistic, but works for illustrative purposes
- Losses not included (but could get this from analytic #3)…

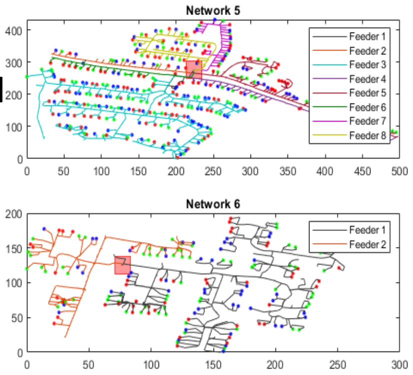
# Analytic #3: LV Digital Twin

**Features**

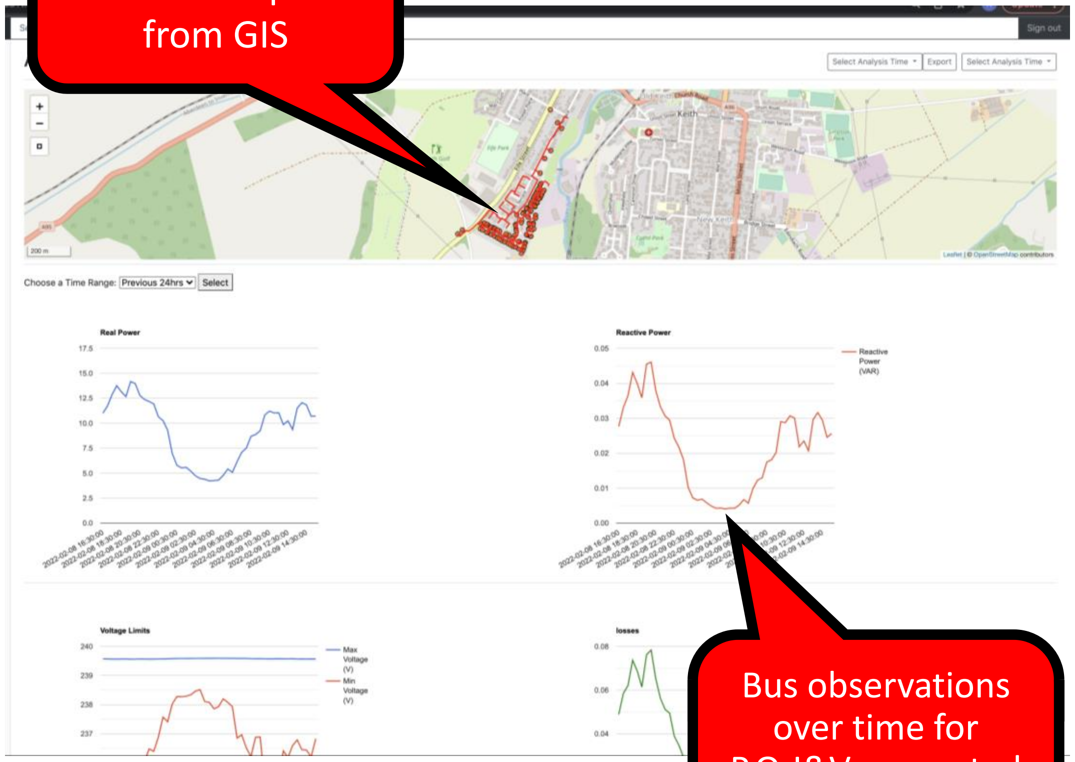
- Network model automatically generated from GIS shapefile data
- MPANs populated with either Smart Meter data or simulated domestic loads
- EPRI OpenDSS solver used (in Lumen, on Cloud)
- 30 minute snapshots of full network observation
- Django based UI runs in web browser

**Applications**

- Heat pump penetration studies – feed through load flow model to get voltage and thermal violation likelihood on a given network
- Mixed low carbon technology analysis; examine combined PV/EV/heat pump network effects




Network circuit of interest – pull from GIS




Bus observations over time for P,Q,I&V generated by OpenDSS network model

In research terms

# NEXT?

# Main Findings

- Won't be able to get fully observed models of power networks at LV
- Can get the networks though – even more viable with digitalisation
- Can hypothesise how these networks will behave under particular loading scenarios
  - Mainly the edge cases
- Unobserved quantities can be recovered through power flow model which ML models (PV estimation, loss estimates, state estimators, hierarchical forecast models, reactive power forecasts etc) can be trained

# Threads left hanging?

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- Informed? Then what?
  - Planning
  - Control
- Even less than very little data?
  - Transfer learning
  - One shot learning
  - Superesolution
- Model said what?
  - Explainability
- Data said what?
  - Provenance and uncertainty

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# AMIDiNe

Analytical Middleware for Informed Distribution Networks

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