WPD INNOVATION

Transforming the electricity network

Project SEAM

Spatially Enabled Asset Management

Dissemination webinar

June 2021

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Our Priority Areas

- Decarbonisation and Net Zero
- Heat
- Transport
- Communities and Consumer Vulnerability
- Data

SEAM Project Overview

Problem statement

- GIS representations of the WPD networks involve large volumes of data and when errors occur these are not always easy to spot.
- The Low Voltage (LV) network is particularly extensive and errors can go undetected as connectivity models were not supported by the previous GIS system.
- Accurate LV representation in particular is critical to support future network investment.
- Inaccuracies in the GIS data could limit ambitions set out in digitalisation strategy, constrain the future build of network topologies that support smart networks and the transition to a DSO and reduce the value and wider use of their data by third parties.

Project SEAM

- While many errors can be found using algorithms, we expect there to be a number of harder-to-fix errors that would benefit from using a wider dataset and machine learning / advanced approaches to identify errors and propose corrections.
- Focus on harder-to-fix errors that draw on multiple datasets and machine learning / advanced approaches to identify errors and propose corrections.
- This would improve the GIS data quality in ways that would otherwise require prohibitive manpower costs to audit the data.
- The ML tool will be applied to LV networks, where errors are expected to be most numerous, and HV and 33kV networks where comparisons can be drawn to the errors flagged within the Integrated Network Model.
- Knowledge share session held with Scottish Power and SSE to share key learnings from SP work and avoid duplication.

SEAM Use Case Groups

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1 Customer Connectivity

- Identify potential errors and link customers to LV circuitry through connection points, where existent in Crown or Electric Office (EO), and also using spatial proximity if there are un-mapped customers.
- Estimate peak demand (i.e. on a winter's evening) up to substation level to identify potential areas in the LV network that the demand surpasses the capacity.
- Infer inaccurate or missing customer attributes with enriched customer datasets.

2 Incorrect or missing asset attributes and missing assets

- Identify missing or incorrect LV asset attributes using EO data and suggest corrections.
- Develop a graph model and apply Machine Learning techniques to identify relationships and patterns in the way that point and linear assets as well as their attributes are connected to highlight potential errors and suggest corrections.

3 Inconsistency across systems

- Where there are disparate systems that store data on the same asset (e.g. EO and CROWN) and there is associated locational data, it can be tested whether this can be used to verify any attributes that are stored in each system.
- Build on the graph model developed in Use Case group 2 by linking with CROWN dataset.

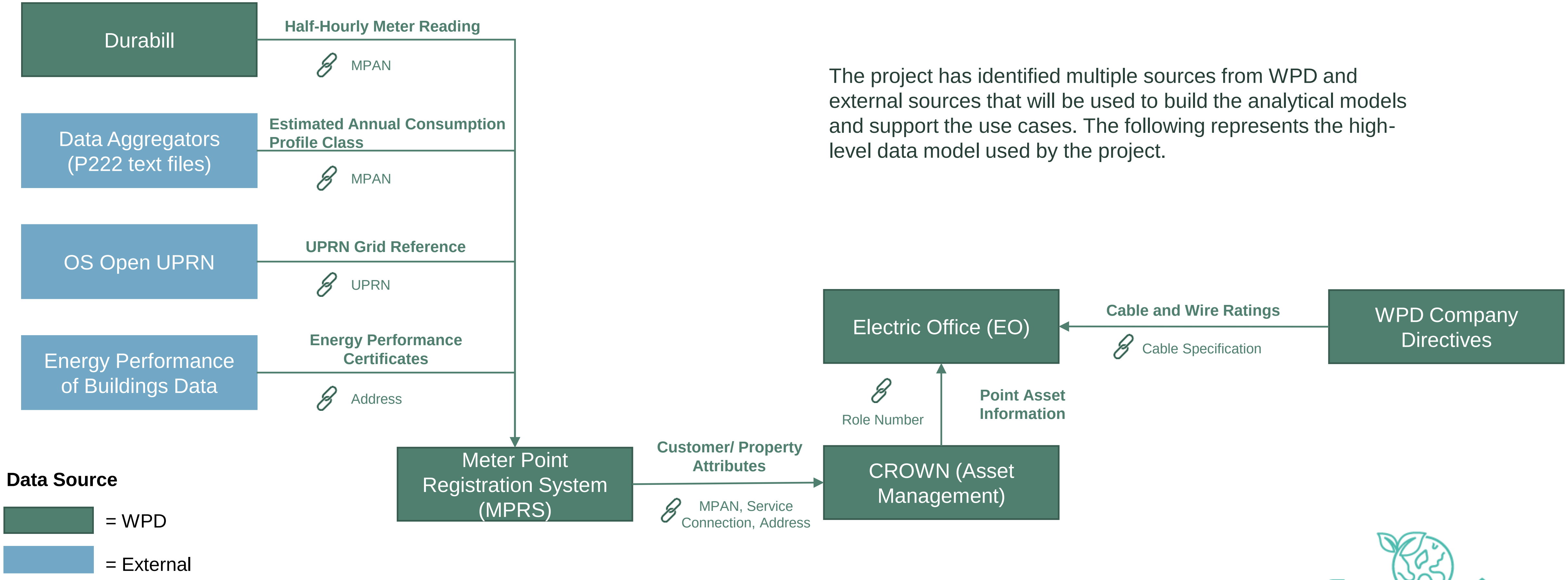
4 Technical inconsistencies

- Building a technical ruleset as well as 'learning' rules from the data to highlight where circuitry built from the GIS data is infeasible
- Use point/line topological graph modelling to assess possible paths from substation to customer to find exceptions where this is technically infeasible, illogical or unlikely

The Use Cases will be developed using the **Barnstaple area** (18km x 15km) and focus on the **LV, 11kV and 33kV** networks (results for the Results for 11kV and 33kV networks will be compared to the data quality issues reported by the Integrated Network Model)

High-level logical data model

The project has identified multiple sources from WPD and external sources that will be used to build the analytical models and support the use cases. The following represents the high-level data model used by the project.



Electric Office data profiling

Network Connectivity | Asset Attributes | Customer Connectivity

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The project has undertaken an initial profiling activity on the Electric Office data for the Barnstaple area (18km x 15km) that has been selected for the proof-of-concept. This is focused on a straightforward set of data completeness measures due to limited understanding of the data at this stage to consider its accuracy and validity.

In this section of the report we highlight key measures from the profiling and its implications for the project:

	Key profiling measures	Summary of key learnings
Network Connectivity	For circuits*, excluding special codes (e.g. non-energised and private): • **1,083** unique circuit IDs: 25 HV, 43 MV, 1,015 LV • **18,473** (47.4%) LV cable and **2,975** (42.1%) LV wire RWO with unknown or missing circuit IDs • **6,667** (23.8%) point assets (Keypole, Power Transformer, Isolating Equipment and Connector Point) with unknown or no assigned circuit ID	• A sufficient completeness of physical circuits is required to understand the relationship between assets in different locations and how this can be pooled and used to improve the data quality in all of those areas. The analytical approaches in Use Cases 1 and 4 in particular are dependent on this. • There remain a significant number of LV cables, wires and point assets with no circuit ID. Our evaluation at this stage is that there is sufficient completeness of the circuits to deliver results for Use Cases 1 and 4 that allow is to evaluate the performance of the analytical approaches. • The WPD Technology Mapping Team are currently undertaking a project to build LV network connectivity in EO (the circuits in our dataset include the outcome of Phase 1 of this project). SEAM is exploring the use of a graph model and physical proximity as a complementary approach to identifying missing circuit IDs.

* Circuit IDs equal to “”, “0/0”, “1/1” and those associated with zero or one wire/cable RWO asset are treated as “Unknown”.

Electric Office data profiling

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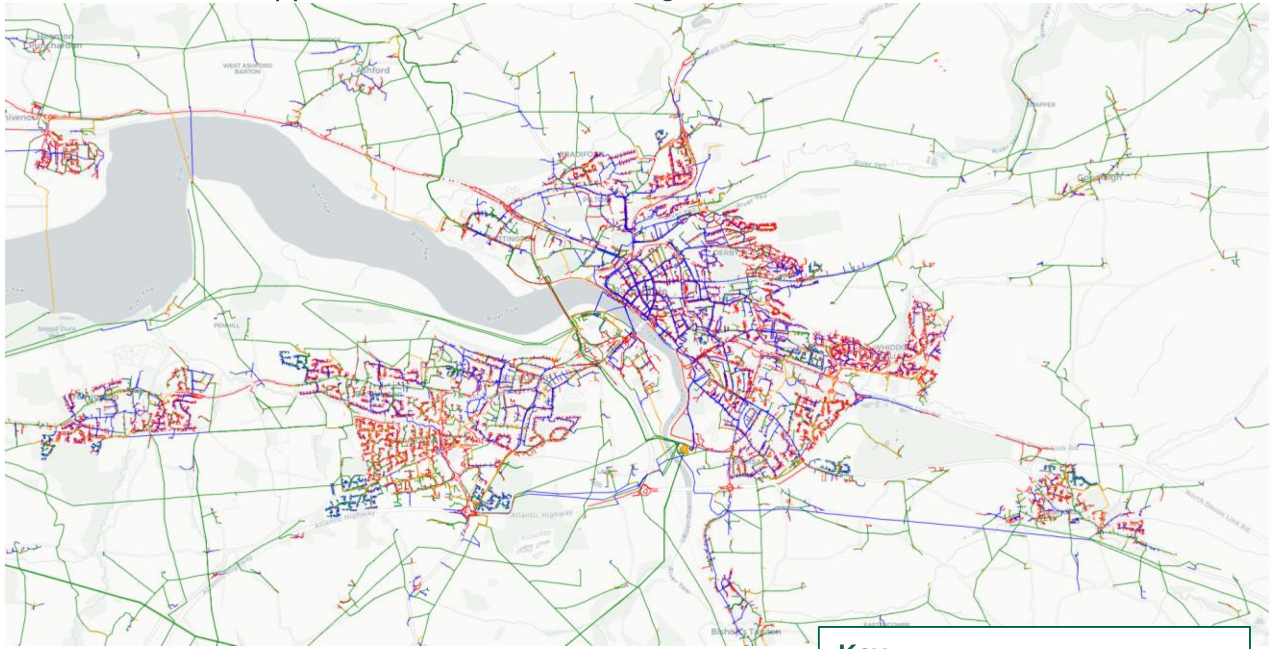
	Key profiling measures	Summary of key learnings
Asset Attributes	• **59.6%** of cables and **22.8%** of wires have an explicit unknown component within the specification attribute. • **40.2%** of cables and **84%** of wires have a size label • **23.8%** of cables and **68.8%** of wires have a type/material label • **80.0%** of cables and **94.0%** of wires have a conductor/wire number label • Cables and wires specification where a combination of two or more labels exists for an asset is less likely. **12.6%** of cable assets and **62.8%** of wires have been found to have all 3 attributes detected within the specification column* • No missing voltages or network types	• The cable and wire specification attributes in EO are a concatenation of three associated components (size, type/material, number of conductors). A significant number of these contain at least one component that is 'unknown' (see next slide). • Extracts from the WPD Directive for cables and wires is used to map current ratings to the assets. The cable and wire ratings depend on size, material, number of conductors, location (i.e. in ground, duct or in air) and season/loading type. • There are no missing voltage or network type attributes which makes these a good candidate to develop a model for Use Case 2.

*number of conductors and size is matched on a regex match, the type/material is matched on type/material found in the WPD directives: SD8B_4_part1 and SD8A_3

Electric Office data profiling

Mapping of cable and wire specification component (size, material/type, no. of conductors/wires) completeness

Barnstaple area specification availability. Overall coverage quality changes depending on area; patchiness of coverage and specification availability suggests that a graph-based / machine-learning approach to labelling missing cable specifications could be more successful than a traditional tabular approach to machine learning.



Specification availability at HV level is high due to previous work done in this area i.e. INM. However, at LV level, the data is less complete and available

Key
- Red: all attributes missing
- Orange: one attribute available
- Blue: two attributes available
- Green: all attributes available

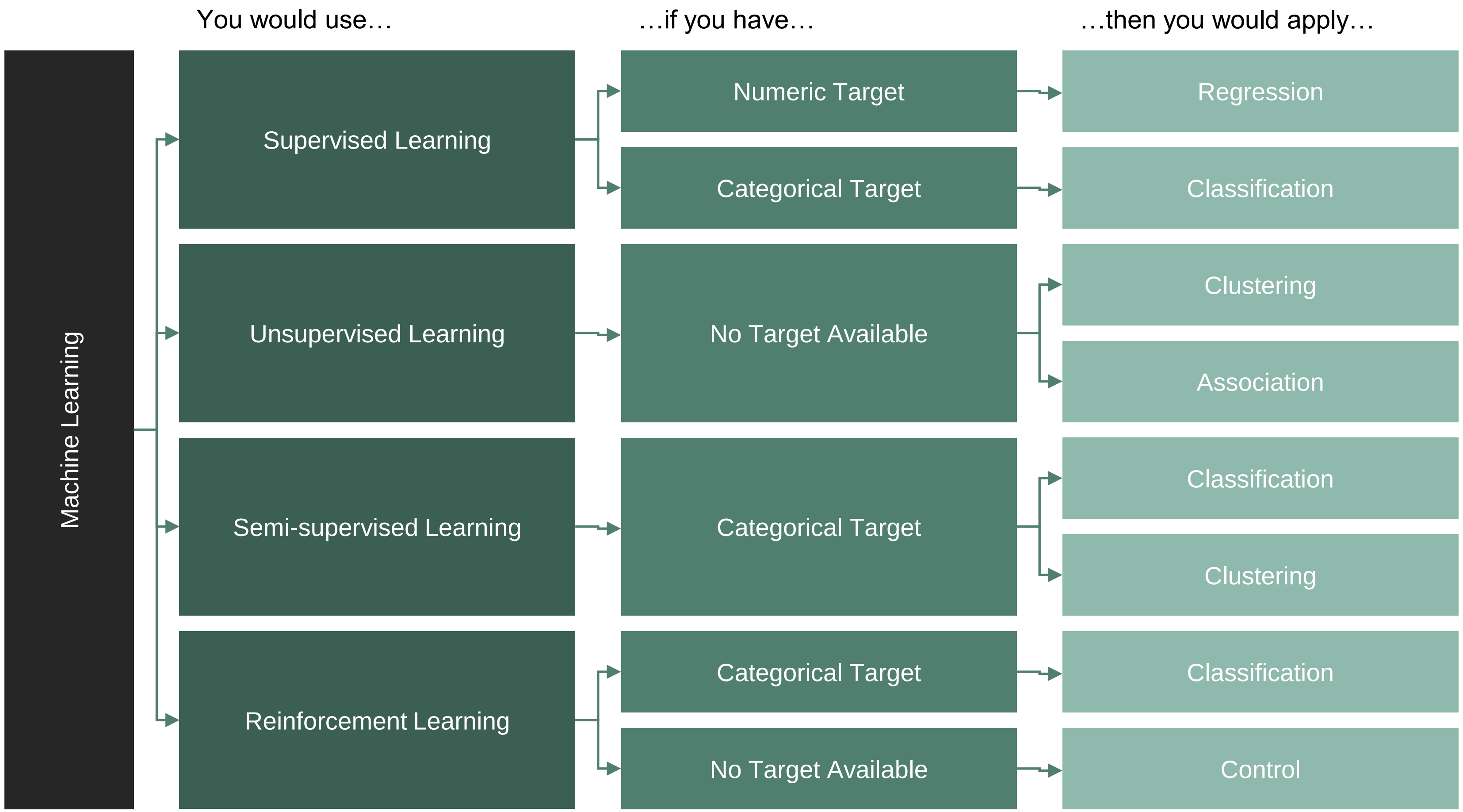
Some areas have good coverage; this area appears to be new build. Even in relatively good areas, some service cables miss one or two attributes

High density areas with all missing does tend to have some assets with good specification availability, potentially owing to the way that cables and wires are labelled in legacy documentation

Electric Office data profiling

	Key profiling measures	Summary of key learnings
Customer Connectivity	• **75,867** MPANs and **54,275** UPRNs (covering the North Devon region that extends beyond the Barnstaple area in scope for the proof-of-concept) • **36,186** domestic and **1,854** non-domestic EPCs for the North Devon constituency (based on September 2020 data). • **28.5%** of MPANs with a missing UPRN	• The project is exploring the use of the Energy Performance Certificate (EPC) dataset to enrich the customer features (issued for domestic and non-domestic buildings constructed, sold or let since 2008). There is a challenge linking this to MPRS data because EPC does not contain UPRN (it includes a unique building reference number that has no relationship with UPRN). Our approach relies on address matching which is not 100% accurate due to differences in formats or structure across datasets. • The address data in CROWN is not well structured (the address is inconsistently ordered across 9 address lines). The use of UPRN and address (from addressbase premium) to match would provide a more structured dataset but this is not available to support the proof-of-concept.

Model selection

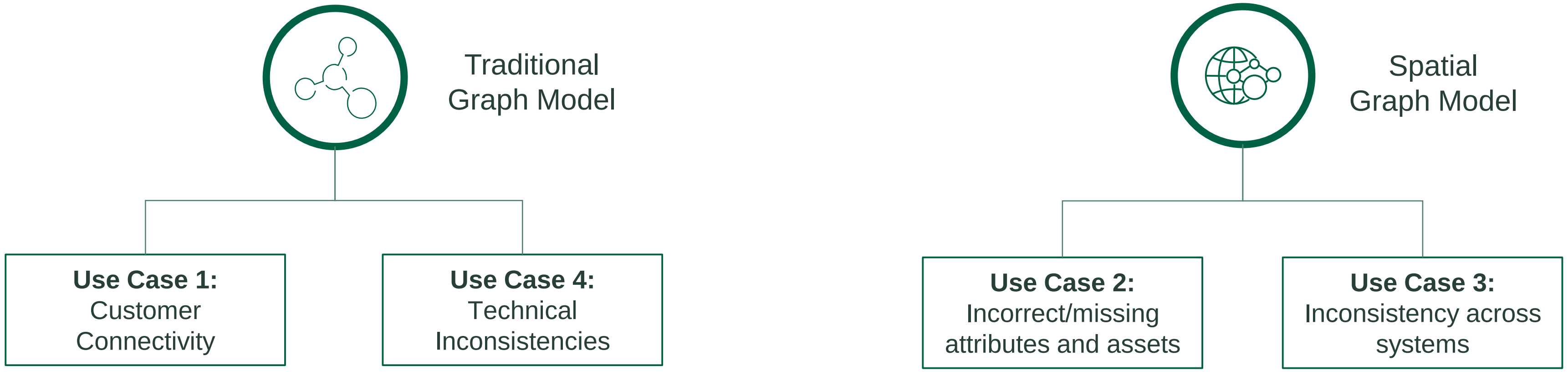


Key considerations:

- Traditional machine learning works with tables of observations, where the absolute values of the attributes can be compared with the other observations in the dataset in order to extract patterns.
- In context of geospatial data the absolute location of each asset is of limited utility on its own: what matters more is the local neighbourhood of each asset, i.e. what are the attributes of the other assets in the surrounding area?
- For power networks, the physical connectivity of the assets is more important than the relative locations. However, constructing this information is difficult if it is not already available, especially in the presence of missing assets.

Model selection

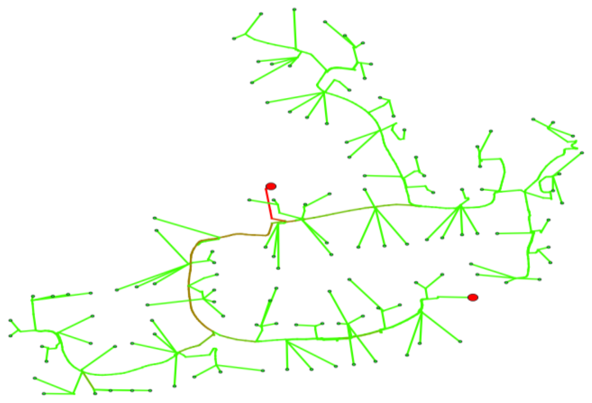
- Our approach to all use cases will utilise a graph model (i.e. based on a connected graph of nodes and relationships with properties and labels). Other applications of graph models in this field include the Integrated Network Model data process and Scottish Power Energy Networks for representing an LV Network as a Network Tree Graph to verification of network cables and topologies.
- Traditional graph models for power networks are focused on power systems analysis and network management, rather than on asset management. They typically rely on electrical properties and require complete electrical connectivity – ignoring spatial relationships. This approach is well suited to Use Cases 1 and 4 where the physical connectivity of the model is central to conducting the modelling or forms a part of the pattern identification.
- One of the key learnings from our initial data exploration is that traditional Machine Learning approaches that work with table-based observations (e.g. regression techniques such as k-nearest neighbours) will have limited usefulness. This was an initial hypothesis and a proposed approach for Use Cases 2 and 3.
- A new graph model is required that is focussed on predicting asset attributes and relationships and emphasises the spatial relationship between assets. This will be a novel approach based on a spatial graph model that contains a layer of point location nodes, with distance relationships between them to create a spatial mesh, and edges between each asset or feature and the location nodes that are part of it.

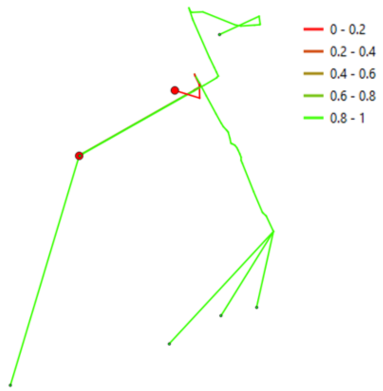


Model 1: Customer Connectivity

Overview of the model

Purpose	• Use the connectivity of assets and customers to perform a simplistic transportation model to verify that the existing assets (and their attributes, i.e. capacity in terms of kW) is configured such than it can supply demand at peak times in the winter for customers connected to the circuit.
Method	• A graph is created for each unique circuit_id (As recorded in Electric Office), wires, cables, customers, substations are connected to the model, where line assets (wires and cables) are edges and point assets / customers are nodes. • Demand is calculated at the customer nodes (either using estimated annual consumption and Elexon profile class or half-hourly meter readings if available) and a network flow problem is configured to determine an optimal strategy for routing power through the network. • Where the network is unable to supply the peak demand this could be the result of an error in the connectivity model resulting in the network appearing to extend further than it's real bounds e.g. in the case of a missing open point.
Benefits / innovation	• The use of a max-flow algorithm means there is now need to carry out a full power-flow analysis. This produces similar results with a simpler, faster model does not require a separate software package and licence. • Clustering algorithm is able to infer implied customer connectivity. • Automates the use of demand data (HH smart meter and Estimated Annual Consumption) and backfill missing cable/wire data from WPD directives.





Model 1: Customer Connectivity

Modelling process steps

1. **Data preparation**

Prepares the datasets and is comprised of a number of merges between data sets, filters, and also calculation of the capacity, with the first stage of capacity backfilling applied, i.e. estimating the capacity where there is not sufficient asset data to confirm the capacity.

2. **Circuit configuration**

The circuits are configured from the GIS data, with connections added to connect some microdisconnects which appear in this data

3. **Process and connect customers**

The graphs configured in the previous section are used to connect customers by adding edges from the customer to the nearest node with degree 1 in the graph. Within this section, the settlement date and period are found for the peak demand for each circuit to calculate the demand per customer at this time.

4. **Locate source / substation in graph**

The substation is located on the graph, given a threshold (default set to 10m).

5. **Run max flow**

A simple graph-structure based backfilling of capacity is applied for specifically synthesized edges which connect the customers to the network as well as edges which connect disconnects. Pre-processing, which is required to simplify the circulation with demand problem to a maximum flow problem, of the graphs is also conducted at this stage.

Model 1: Customer Connectivity

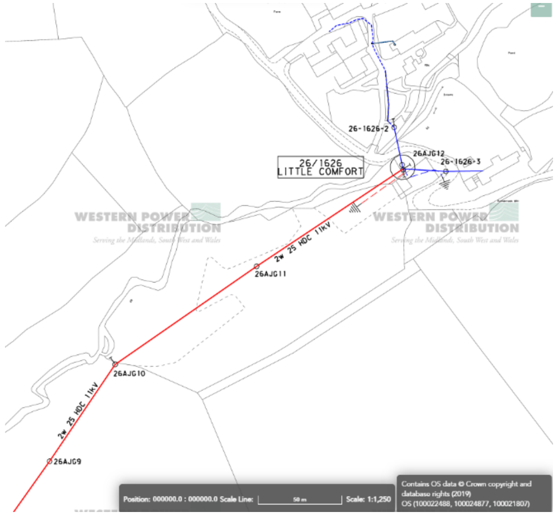
Output reports

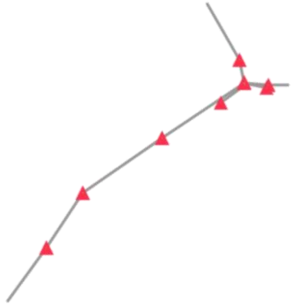
Report Name	Purpose
1. New edge location	This report contains all edges added to each circuit (circuit_id) as part of the circuit config stage. Edges are added if the addition of this set of edges connects all isolated graphs for the circuit with circuit_id. These are indicators of where there may be microdisconnects in the underlying data.
2. Customer connections	This report contains all edges added to each circuit (circuit_id) as part of the customer connectivity stage. All edges are kept, so that the user can use this report to cross reference against the reports ‘line’ and ‘point’ and decide on a threshold distance by filtering using standard data processing software such as Excel. This information would help data stewards identify unexpectedly missing service cables in areas where this was generally available.
3. Customer exceptions and matches	These reports contain customers (half hourly and estimated annual consumption) which were not or were matched to any of the circuits (circuit_id). Again this would be indicative of missing service cable data though it may also indicate incorrect network association within CROWN.
4. Max flow report	This report shows the metrics of each stage of building the circuits per circuit_id and the number of customers and wires that are exceptions within each circuit. This report is intended to be used alongside ‘line’ and ‘point’ to investigate exceptions.
5. Line and Point	These Geopackages comprise of linear and point assets within Electric Office which were used in the connectivity modelling, detailing a number of attributes which were generated / inferred / backfilled during the modelling process as well as the results of the max-flow analysis.

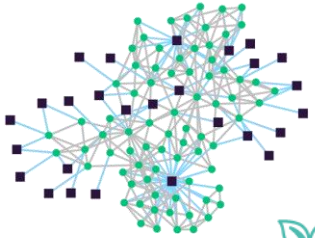
Model 2: Spatial Graph Model

Overview of the model

Purpose	• The main purpose of the spatial graph model is to identify incorrect and missing attributes in the GIS data and to suggest correct values through the application of machine learning (graph neural network) using a graph data structure.
Method	• The model is inductive, which means that a trained model can be applied to unseen data without retraining. Hence, the model can be trained on a subset of the network and then used to create predictions for other parts of the network. • An inductive, machine-learning-based model with three separate, but related, processes: Training, Evaluation and Prediction. • For each prediction, the model also produces confidence scores that can be used to filter or rank the predictions. These are obtained from the raw outputs of the neural network. • There are three trained sets of thresholds that the user can choose between to determine the required level of confidence required for a suggestion to be included in the detailed exceptions report.
Benefits / innovation	• Does not require information about electrical connections, • Supports all kinds of assets, attributes and relationships, • Supports external geospatial data • It can be constructed using only a subset of the assets, attributes and features.







Model 2: Spatial Graph Model

Modelling process steps

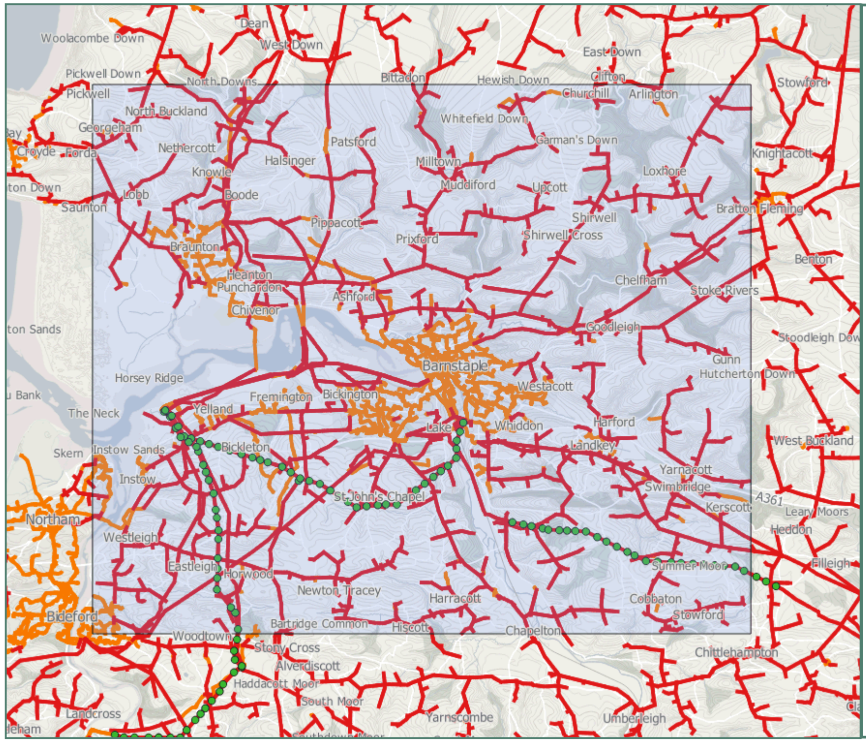
1. **Initialisation**. Process input arguments, load parameter file and model file (if applicable) and prepare internal state of the model application.
2. **Load data**. Read EO asset data from file and prepare for modelling.
3. **Prepare graph data**. Extract and convert node and edge data from EO data. Generate synthetic errors (if applicable).
4. **Make graph**. Construct graph data structure and organise data for training and evaluation.
5. **Train model**. (If applicable) Train neural network model and score thresholds, and save to file.
6. **Evaluate model**. Calculate predictions for all assets in dataset and check score thresholds.
7. **Create reports**. Create detailed and summary output reports as CSV and GeoPackage (as appropriate).

Model 2: Spatial Graph Model

Output reports

Report Name	Purpose	Description
Detailed		
Model Outputs	Understanding all the outputs from the model	All relevant inputs and outputs from model. All the other reports are a subset or summary of the data in this report.
Exceptions Report	End user investigating suggested changes to the GIS data	All rows from model_outputs where output value is different from input value and score meets criteria. Excludes columns that are not interesting for the end user.
Evaluation Report	Understanding the behaviour of the model in response to simulated errors	All rows with non-missing values in the original data. Only produced when synthetic errors are added to the input data.
Summary		
Exceptions Summary	End user understanding the distribution of identified errors across asset types and attributes	Number of rows with each error_code value (see below) for each asset type for each attribute.
Evaluation Summary	Understanding the overall performance of the model on simulated errors for different asset types and attributes	Accuracy (proportion exactly correct) for each asset type and attribute for each error_code. Only produced when synthetic errors are added to the input data.
Classification Report	Understanding the overall performance of the model on simulated errors for different attributes and attribute values	Classification report (see below) for each attribute. Only produced when synthetic errors are added to the input data.

Model demonstration and sample error investigation



1. Demonstration of the Excel User Interface and running the SEAM models

2. Investigation of sample errors

Model 1: Customer Connectivity

Summary of results

Summary:

- 27 circuits were found to have power flow violations with customers not being supplied their full demand
- 61 circuits were found to have cables/ wires with head room percentage below threshold set at 20%

Observations:

- There are some circuits where configuration looks reasonable upon examination and violation is happening at the feeder where headroom is low due to demand supply requirements
- Circuits where there are clear missing cables / wires connecting to customers and load is concentrated on a line asset where in reality this load may be distributed
- A large number of the violations are happening due to the way capacity is being backfilled for unknown current ratings for wires and cables at LV, where there is data on the wire and cable specifications, this is not conforming to directives. The cable capacities are then backfilled according to the circuit aggregation method chosen by the user, if this is not available then area wide is used: for customer connections, a neighbors aggregation

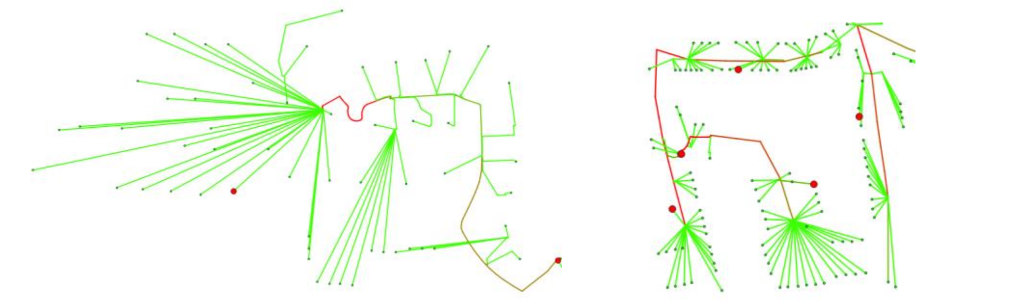


Figure 1: Missing cables / wires to customers causing clusters of customers at the ends of cables, causing overload

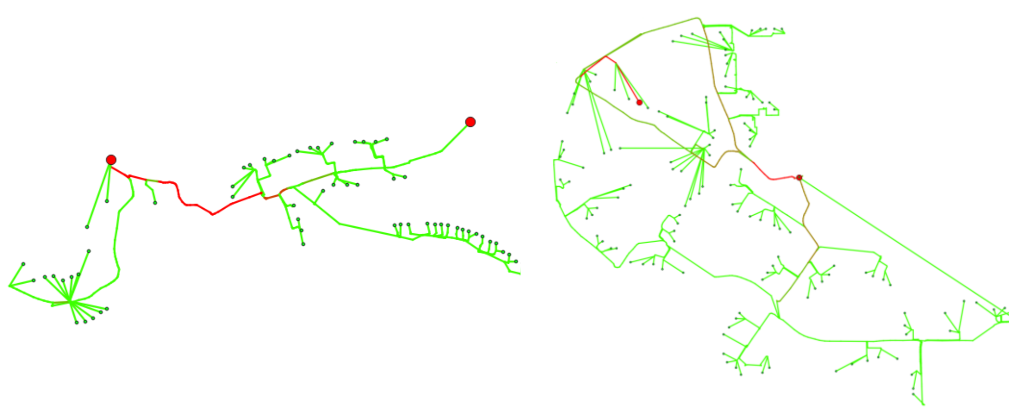


Figure 2: Connected circuits with capacity bottleneck at feeder where circuit configuration seems realistic

Model 1: Customer Connectivity

Key observations and project learning

Summary of key observations and learnings:

- Max flow is fast (data preparation and post processing phases take the majority of the model running time) for a simple transportation problem which is suitable for studies without the need for considering extreme events and useful within the reconciliation process / data verification using the technical feasibilities of the circuits.
- The method can be used to highlight particularly important assets that have a high impact on the circuit, i.e. where there may be potential bottleneck in a circuit and verification is required that its specifications are correct for the technical operation of the circuit. The method is also useful to ensure that the most critical assets are highlighted.
- The method is robust to different topologies and configurations of the networks, accommodating radial and mesh and can be used in a number of different scenarios where data on network topology may not be of high quality or complete.
- The use of this model could be more iterative in nature, with a data steward checking violations, updating Electric Office where violations may be caused by configuration, specifications and re-running the model to see the improvements made and reduction in violations.
- The ability to eliminate reasons for violations (customer wrongly assigned, profile class wrongly assigned, EAC or half hourly consumption error, for example) is diminished due to the level of missing assets (cables and wires to create connectivity and connections to customers) and missing labels for cable and wire specifications. Again, this suggests that an iterative approach may be useful where this data is progressively added.
- There are few ‘true’ violations of network capacity indicated in the data as mostly the components of the network flagged as bottlenecks are where capacity values have been or reflect simulated cables / wires or the simplifying assumptions used to model ways in which customers are connected.

Model 2: Spatial Graph Model

Summary of results

Training

- Accuracy when predicting “no_error” is very high (generally >98%).
- Accuracy among “high scoring” errors is generally higher (sometimes considerably) than the “low scoring” errors.
- Accuracy when filling missing data is much higher than the majority class percentages.
- Accuracy when prediction “wrong value” is generally higher than the majority class percentages, with a few exceptions.
- Accuracy for rare attribute values (< 200 examples in training dataset) tends to be much lower
- These observations are confirmed using different synthetic errors on the same area (i.e. using the evaluation process).
- The exact numbers are based on the synthetic error generation process

	no error	missing value	wrong value	missing value low	wrong value low
network type	99.87%	98.66%	98.00%	92.09%	75.93%
nominal voltage pp	98.71%	94.46%	83.08%	77.01%	52.33%
spec material	99.21%	88.72%	70.93%	51.09%	32.76%
spec size	97.88%	71.30%	44.07%	42.82%	19.40%

Model 2: Spatial Graph Model

Summary of results

asset type	attribute name	no error	missing value	wrong value	missing value low	wrong value low
cable	network type	39001	0	31	0	45
	nominal voltage pp	38596	0	171	0	310
	spec material	9228	19467	41	10248	93
	spec size	12181	12600	197	13850	249
connector point	network type	15442	0	1	0	0
	nominal voltage pp	15392	0	9	0	42
connector segment	network type	7688	0	2	0	40
	nominal voltage pp	7712	0	7	0	11
energy consumer	network type	231	0	0	0	0
	nominal voltage pp	230	0	0	0	1
energy source	network type	2	0	0	0	0
	nominal voltage pp	2	0	0	0	0
isolating eqpt	network type	3984	0	64	0	24
	nominal voltage pp	3992	0	27	0	53
keypole	network type	4724	0	0	0	0
	nominal voltage pp	4715	0	0	0	9
pole	network type	4534	3161	1	753	1
	nominal voltage pp	4523	2235	4	1679	9
protective eqpt	network type	2435	0	16	0	155
	nominal voltage pp	2493	0	21	0	92
service point	network type	2512	0	0	0	0
	nominal voltage pp	2511	0	0	0	1
tower	network type	82	0	0	0	0
	nominal voltage pp	82	0	0	0	0
wire	network type	11150	0	3	0	24
	nominal voltage pp	10561	0	298	0	318
	spec material	7586	1211	66	2235	79
	spec size	8389	1214	140	1222	212

Prediction

- Vast majority of attributes were identified as “no error”.
- Based on spot-checks, many of the suggested corrections look right or plausible. Those that don’t seem like artifacts of the current synthetic error generation or associated with the limited information given to the model.
- Suggested changes to network type were mostly LV → MV. Anecdotally, many of these are associated with pole-mounted substations, which is hard for the model since there are a few LV assets close to several MV assets and the power transformer nodes are not currently included.
- Suggested changes to nominal voltage pp are mostly 230V → 400V, with 400V → 230V, 400 → 11kV and 230V → 11kV being the next most common (in order).
  - Discriminating between 230V and 400V conductors can be hard for the model, since they may be directly connected and attributes relating to phasing and usage are not currently included.
  - The changes from LV to MV network voltages are often associated with the same change of network type mentioned above.
- Suggested changes to material and size are hard to assess independently. However, the main observation is that Earth wires ought to be treated separately from the other conductors, e.g. as a separate asset type.

Model 2: Spatial Graph Model

Key observations and project learning

Summary of key observations and learnings:

- It is possible to train an inductive graph neural network-based machine learning model to identify and correct missing and erroneous data in a power distribution network.
- The model can produce useful suggestions using only a limited number of attributes and the geospatial relationships, which all come directly from the Electric Office (EO) dataset.
- The model has identified some individual cases and some groups of cases where there appears to be errors in the EO extract used for the project.
- The overall performance of the current model supports the aim and learning objectives of the PoC. Further enhancements to the model performance should be considered as part of a transition into Business-as-Usual (BaU).
- Enhancing the model with additional attributes, nodes and edges is expected to incrementally improve the performance. In particular, some candidate enhancements have already been identified that should improve the performance for the main groups of incorrect predictions discussed in this document.
- The spatial graph structure and graph neural network are a flexible basis for adding a range of data and predictions.
- The model is fast: prediction runtime is dominated by reading and writing the GIS files and pre-processing the geospatial data, and model training can be completed in a reasonable time on a standard laptop (for the scope of this PoC).

Project outcomes (1/2)

Summary of key project outcomes	
1	An assessment of WPD initial data evaluation in the trial area has been made as part of the Interim Learning Report. This has provided an overview of the completeness of the different datasets and proportions of different asset types between the voltage layers rather than commenting on the accuracy of the data presented.
2	The types of error that can affect the GIS data have been documented as use cases and grouped together to allow for mapping between use case groups and potential evaluation methods. This is likely to be transferrable knowledge to other DNOs.
3	Interim learning has been shared with other DNOs that have already carried out work in this area or are planning to in order to avoid duplication of effort.
4	The applicability of AI approaches to identifying and suggesting corrections to GIS errors has been confirmed.
5	Two complementary modelling approaches have been selected and the rationale for their selection has been documented and shared.
6	The PoC model has been developed and tested both by Capgemini staff and on WPD hardware with a configuration that does not require access to the internet by WPD staff.
7	The accuracy of the PoC models has been evaluated and shown to be above that achieved by assuming the most frequently occurring result.
8	The results of the models have been evaluated and confidence metrics have been used to separate values with high and low confidence. The separate groups are seen to differ in accuracy with the high confidence group achieving better results than the low confidence group, confirming the usefulness of the confidence metrics.

Project outcomes (1/2)

Summary of key project outcomes	
9	Reports from using the model have been passed back to the business to allow identified errors and proposed corrections to be examined further with a view to correcting the errors identified.
10	Comparison with INM errors has shown that the different approaches are complementary.
11	Suggested priorities for BAU implementation and further analysis likely to improve data accuracy have been proposed
12	Learning has been disseminated via published reports and a webinar enabling other DNOs to build on the learning generated by the project without duplicating the work.

Business-as-usual and future recommendations

Transition to BaU:

Process for resolving data issues

- Establishing a process for reviewing potential corrections to errors and missing values identified by the models.
- For some issues there may be sufficient contextual information in the data for a person to confirm or reject proposed values without requiring a site visit – but direct validation may not always be possible (e.g. underground assets)
- Representation of source GIS data (assumed to be captured at installation) and modelled values with confidence in Electric Office.
- Potential for alternative methods to validate LV network connectivity (e.g Scottish Power use of smart meter data).

Technical integration

- Four key areas of activity: Integration, Productionisation, User Interface and Deployment.

Future development recommendations:

Recommendation	Priority	Effort
Feedback from users	High — sets direction for next phase	Low — based on existing deliverables from this phase
“Quick wins”	High — directly addresses some findings from this report	Low — changes have already been identified and are relatively straightforward
Combine models	High — increases the performance of the models	Low — mostly makes use of existing functionality
Scale-up	Medium — increases the scope of the model	High but flexible — many different options within this category
Blue skies	Low — exploits the model for new use cases	N/A

Project Evaluation Report contains detailed description of future development recommendations.

Thanks for listening

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