

WP5 D1 Report

Integrated phase identification and rural capacity release

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Internal

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1 Executive Summary

WP5 looks at combining WP3 and WP4 approaches to lead to more insightful outcomes and outlines how this would move from method demonstration to a practical capacity-release workflow for rural HV feeders. WP3 provides electrical phase evidence from smart meter voltage correlation, while WP4 provides physical conductor evidence from machine vision and aerial imagery. Combining both evidence streams in a common network graph creates a stronger basis for assigning phase, identifying record discrepancies, and locating feeder sections where phase unbalance is limiting usable headroom.

The business opportunity is not simply better phase labelling. It is the ability to find where capacity is trapped on rural lines because load is concentrated on one phase while the adjacent phases still have usable headroom. By converting phase identification into branch-level loading and confidence metrics, NGED can prioritise low-cost interventions such as phase swaps, targeted validation, and record updates before defaulting to wider reinforcement.

The recommended next step is a focused pilot across a representative 10-15% of the network, targeted at rural feeders with high single-phase spur density, known connection pressure, or visible unbalance in existing analysis. The pilot should use one integrated approach, with clear decision gates, and should produce outputs that can be used by planning, connections, asset data, and field teams.

1.1 Executive recommendation

- Proceed with an integrated WP3/WP4 pilot focused on single-phase HV spurs downstream of tee points, rather than attempting to populate whole feeders where that does not support a practical intervention.
- Use branch-level phase loading, confidence, and degree-of-separation metrics to rank capacity-release opportunities.
- Design the pilot outputs as production artefacts: an updateable network graph, a capacity-release dashboard, a validation register, and an Electric Office correction workflow.

1.2 Abbreviations

Term	Definition
BAU	Business As Usual
CB	Circuit Breaker
CIM	(IEC 61970/61968/62325) Common Information Model for the electricity industry.
CSV	Comma-Separated Value
DCC	Data Collection Company (for SM data)
DD	Data Dictionary
DER	Distributed Energy Resource
DMS	Distribution Management System (such as GE PowerOn)
DNO	Distribution Network Operator
EAC	Estimated Annual Consumption
EAM	Enterprise Asset Management (such as ARM, SAP or Oracle)
EO	Electric Office (NGED's GIS)
ERD	Entity-Relationship Diagram
ETL	Extract, Transform, and Load
GIS	Geographic Information System (such as ESRI or GE Electric Office/Smallworld)
GUID	Globally Unique Identifier

Term	Definition
HH	Half-Hourly
HV	High Voltage
IEC	International Electrotechnical Commission
INM	Integrated Network Model
JSON	JavaScript Object Notation
LCT	Low-Carbon Technology e.g. heat pumps, electric vehicles or photovoltaic generation
LV	Low Voltage
MC	Measurements Calculator
MDM	Master Data Management
MPAN	Meter Point Administration Number (core – the 13-digit format)
NGED	National Grid Electricity Distribution
NHH	Non-Half-Hourly
NIA	Network Innovation Allowance
NOP	Normally Open Point
ODS	Operational Data Store
OGC	Open Geospatial Consortium
RDBMS	Relational Database Management System
RMS	Root Mean Square (= $\sqrt{\frac{1}{n}\sum x^2}$)
RMU	Ring Main Unit
SCADA	Supervisory Control and Data Acquisition
SM	Smart Meter
SMITN	Smart Meter Innovations and Test Network
SS	Secondary Substation
SQL	Structured Query Language
TK	Unique INM Record Identifier
Tx	Transformer
URI	Uniform Resource Identifier
UUID	Universally Unique Identifier
VIPQ	Voltage, Current, Active, and Reactive Power
WKT	Well-Known Text (an OGC spatial geometry representation format)

2 Business Case

Combining the WP3 smart-meter methodology with the WP4 machine-vision methodology creates a practical route to release more usable capacity on rural HV lines. The combined approach improves confidence in phase assignment, exposes localised phase unbalance that is hidden in feeder-head averages, and provides a repeatable evidence base for targeted operational and planning actions.

2.1 Capacity release value for rural feeders

Rural HV feeders commonly include long radial sections and many single-phase spurs. In those conditions, available capacity is often constrained by the most heavily loaded phase on a local branch, not by the total demand connected to the feeder. A branch may therefore appear acceptable at the primary substation while still limiting new connections, low-carbon technology uptake, or voltage performance downstream.

The integrated WP5 workflow turns phase identification into a capacity planning tool. It can show which phase each single-phase spur is likely to use, how confident that assignment is, how demand accumulates upstream, and where moving load or correcting records could release practical headroom. This allows NGED to target lower-cost interventions before committing to broader reinforcement.

2.2 How the approach releases capacity

- Identify local phase unbalance along the feeder, not only at the primary substation.
- Highlight single-phase spurs where load can potentially be moved from a constrained phase to an underused phase.
- Prioritise field validation where the benefit is high and the phase evidence is uncertain.
- Correct network records that currently force planners to use conservative assumptions.
- Create an updateable evidence layer that can support future connection studies and targeted reinforcement decisions.

Benefit lever	Business value	WP5 evidence required
Phase balancing of single-phase spurs	Releases usable headroom on constrained rural branches and can reduce the need for broad feeder reinforcement.	Validated phase assignment, branch demand, and confidence score.
Targeted field validation	Focuses survey effort on the sites most likely to unlock capacity or correct a material planning assumption.	Degree of separation, disagreement flags, and imagery/smart-meter coverage.
Electric Office record correction	Improves planning models, reduces manual checking, and prevents capacity being understated by data errors.	Mismatch register linking physical conductor evidence to asset records.

Connections and LCT readiness	Supports faster connection decisions by showing where spare phase headroom exists on rural lines.	Branch-level headroom view with traceable assumptions.
Production monitoring	Creates a repeatable process for keeping phase records and capacity diagnostics current as the network changes.	Governed data model, refresh process, and exception workflow.

3 Prior Work

3.1 WP3

WP3 developed and evaluated a smart meter-based methodology for identifying the HV phase connections of single-phase distribution transformers. The approach is based on selecting a representative three-phase distribution substation on each HV feeder to act as a reference. Where LV monitoring data is available, the monitored phase voltages are used as the reference; otherwise, representative smart meter voltage profiles from the three identified phase groups are used. The voltage time-series of smart meters connected to single-phase distribution transformers are then correlated against the three reference phases to determine the most likely HV phase connection. Several approaches for selecting the reference substation and reference smart meters were investigated to maximise the robustness and accuracy of the methodology, together with comprehensive data validation and preprocessing techniques to ensure reliable phase identification.

3.2 WP4

WP4 used CGI Machine Vision to process images from helicopter survey images for 5 feeders. Images of line intersection poles were found, and the conductor connections were mapped. 236 images were found with 95 poles from approximately 130,000 images.

While the conductors could be mapped for the available images, due to the nature of the surveys there were a limited supply of images with intersection poles.

4 Comparative Analysis WP3 and WP4

The smart meter and machine vision methodologies produce results at different levels of the network and therefore required additional processing before they could be directly compared and integrated. The smart meter methodology produces phase assignments for single-phase distribution transformers, whereas the available machine vision outputs identify conductor connections at tee points where single-phase HV spurs connect to three-phase HV feeders. To align these outputs, an HV network model was used to trace the connectivity from each identified tee point to the corresponding single-phase distribution transformer. Electric Office (EO) network data was also used to associate poles with their connected single-phase substations, enabling the conductor connections identified at each tee point to be propagated to the associated transformer. This produced a common dataset that allowed the physical conductor connections derived from the machine vision methodology to be directly compared with, and integrated alongside, the electrical phase assignments obtained from the smart meter methodology.

4.1 Constructing a Base Network Graph

To compare and integrate the results from WP3 and WP4, a network graph was constructed to enable the Machine Vision results to be propagated from the identified tee points to the corresponding single-phase distribution transformers. The graph was built using the upstream and downstream bearing information derived for each pole. By matching the downstream bearing of one pole with the upstream bearing of neighbouring poles, accounting for the expected 180° change in direction between successive poles, the connectivity of the overhead network could be traced. Each identified connection was represented as a directed edge between two poles, creating a network graph with defined upstream and downstream relationships. This directed graph was subsequently used to trace the network from the three-phase to single-phase HV spur tee points to the associated single-phase distribution transformers.

Figure 1 demonstrates this property of the bearings.

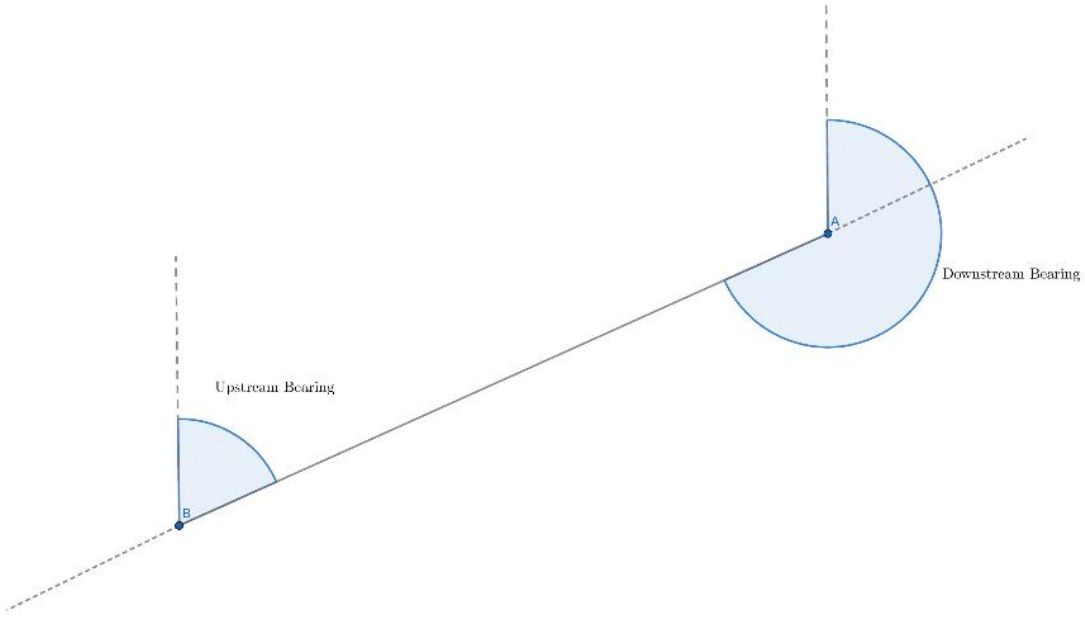


Figure 1: Visualisation demonstration the property of matching bearings

The result of this process can be seen in Figure 2.

4.2 Populate Base Network Graph with WP4 Results

Building on the base network graph, the results from WP4, and the extracted transformer data can be applied and propagated throughout the directional graph. The data is inserted into the network where the pole ID matches across all data structures as seen in Figure 2. Using the inserted data and the directionality of the graph, the remaining nodes can be populated through walking the graph and propagating the known data through inheritance.

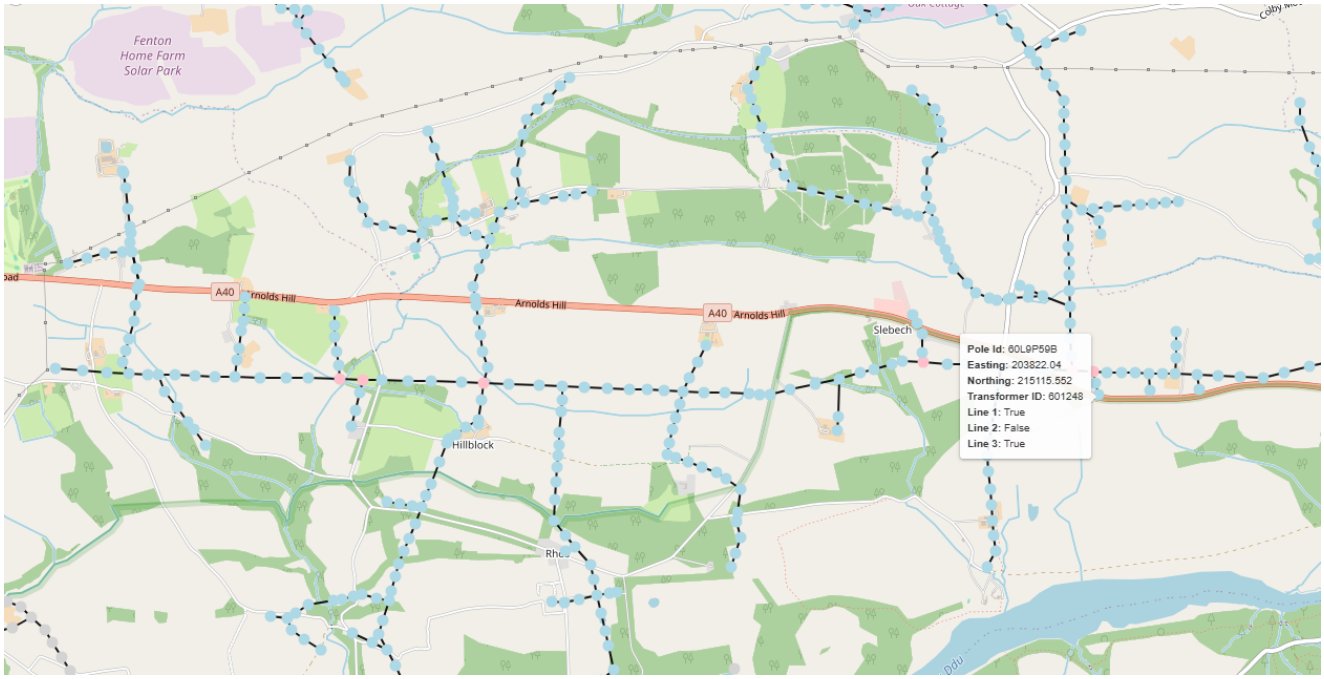


Figure 2: Visualisation of populated network graph for feeder 600017/0034. Poles with data from WP4 are highlighted in pink.

Through this process all poles within the network are assigned wires that could be present at that point in the network. By the nature of the limited data available to generate the WP4 results, the further downstream from the known data a pole is in the network the more uncertain the wire availability is. To quantify this uncertainty, the degree of separation for each transformer is calculated by counting the number of intersections within the network are present between the transformer and a pole with known data. Figure 3 demonstrates how the degree of separation is derived.

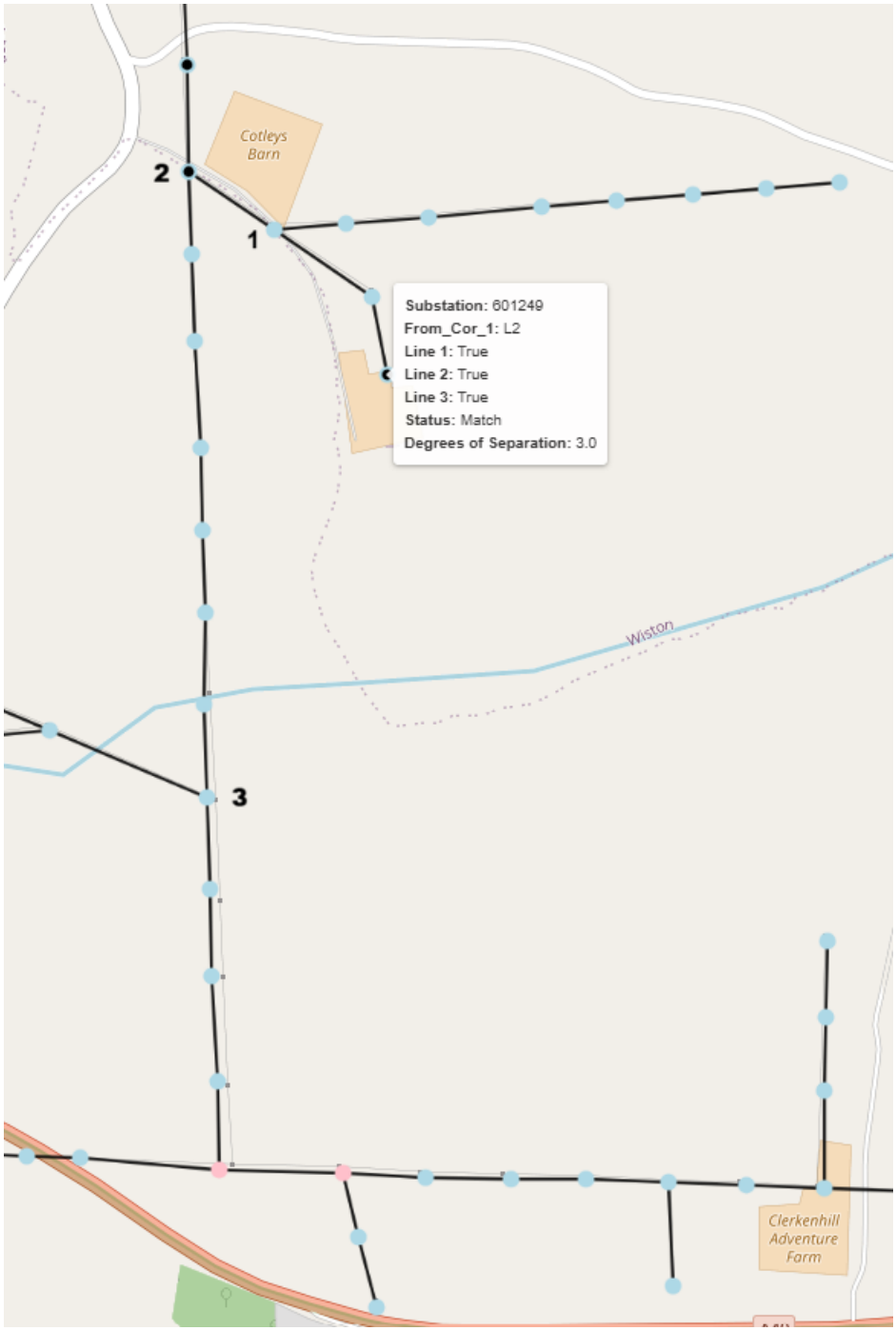


Figure 3: Demonstration of how the degrees of separation value is derived

4.3 Comparative Analysis

From the Machine Vision perspective, the phase connection is identified by observing which two conductors of the three-wire HV feeder are connected to the single-phase HV spur. Assuming the conductor ordering L1 (right), L2 (middle), and L3 (left) when viewed facing away from the primary substation, a spur connected to the L1-L2 conductors is observed as the right and middle conductors, while connections to L2-L3 and L3-L1 correspond to the middle-left and left-right conductor pairs, respectively. From the smart meter perspective, these same HV conductor pairs are observed on the LV side where the L1-L2 HV connection corresponds to the LV phase L1, L2-L3 corresponds to LV phase L2, and L3-L1 corresponds to LV phase L3. If it is assumed that this common convention applies throughout the network, this enables the outputs of the two methodologies

to be directly compared and integrated. However, we recognise that there may be instances where this convention does not apply.

4.3.1 Integrated Phase Identification Using Smart Meter and Machine Vision Data

Figure 4 presents an example where the smart meter and machine vision methodologies produce consistent phase identification results. The machine vision approach identifies that the single-phase HV spur is connected to the L1-L2 conductor pair of the three-phase feeder, while the smart meter methodology assigns the corresponding single-phase distribution transformer to LV phase L1, which, under the adopted phase convention, corresponds to the L1–L2 HV conductor pair. The agreement between these two independent methodologies provides increased confidence in the identified phase connection.

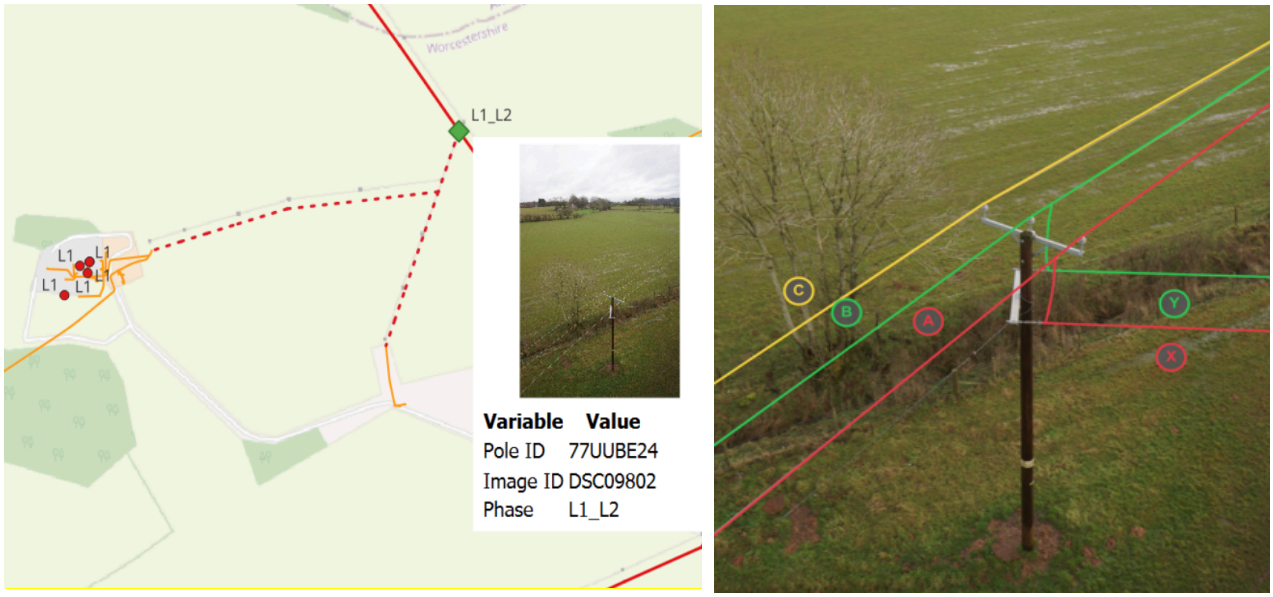


Figure 4: Integrated Phase Identification

4.3.1.1 Investigation of a Phase Assignment Disagreement

Table 1 summarises the comparison between the smart meter and machine vision methodologies for the three feeders where results were available from both approaches.

Primary Feeder	Substation Matches	Substation Total	Accuracy
417560/0041	5	7	0.714
600017/0034	2	11	0.182
770003/0001	5	9	0.556

Table 1: All Substation Comparison (excluding MV = 3PH)

Although the initial agreement appears relatively low, investigation of the disagreements showed that the majority fall into a small number of categories.

The first category consists of transformers where disagreement between the two methods is driven by uncertain smart meter phase assignments. Figure 5 presents an example where the machine vision and smart meter methodologies disagree on the phase classification of a transformer. The machine vision methodology identifies the connection as a single-phase, whereas the smart meter methodology classifies the transformer as three-phase.



Figure 5: Phase Assignment Disagreement

Inspection of the aerial imagery confirms that the pole is single-phase, supporting the machine vision classification. To investigate the discrepancy, the smart meter phase assignments contributing to the transformer classification were examined. Table 2 summarises the three smart meters associated with the transformer together with their phase correlation values.

primary feeder	substation	device	corr_L1	corr_L2	corr_L3	phase
417560/0041	411100	1	0.873	0.766	0.782	L1
417560/0041	411100	2	0.567	0.584	0.648	L3
417560/0041	411100	3	0.721	0.627	0.637	L1

Table 2:Smart Meter phase correlation

The results show that one smart meter exhibits a strong phase correlation, clearly identifying phase L1. The smart meter assigned to phase L3, however, has consistently low correlation values across all three phases, making its phase assignment highly uncertain. In addition, no location information is available for this device in the CROWN data, raising the possibility that it has been associated with the wrong substation. If this low-confidence smart meter is excluded from the analysis, the remaining smart meters both identify phase L1, bringing the smart meter results into agreement with the machine vision classification. This example highlights how combining the two approaches provides a practical means of identifying anomalous phase classifications and flagging devices that warrant further investigation.

A second category of mismatches consists of transformers where the two methodologies disagree only between phases L1 and L2.

Figure 6 illustrates the relevant section of feeder 600017/0034, showing that 9 mismatches originated from transformers supplied downstream of the same tee point, with every transformer tracing back to a single machine vision reference point at pole 60L9P32. As shown

in Table 3, the smart meter methodology consistently identified these transformers as connected to LV phase L2 (corresponding to the L2–L3 HV conductor pair), whereas the machine vision methodology identified the supplying HV spur as connected to the L1–L2 conductor pair.

Transformer/Substation ID	WP3 Result	Pole ID	L1	L2	L3	Match	Degree of Separation
601169	L2	60L4723P2	True	False	False	False	3
601172	L2	60L4722P32	True	False	False	False	6
601179	L2	60L4626P5	True	False	False	False	2
601164	L2	60L4723P9	True	False	False	False	4
601167	L2	60L4722P20B	True	False	False	False	4
601174	L2	60L4722P40	True	False	False	False	6
601163	L2	60L4722P2A	True	False	False	False	1
606588	L2	60L4625P15D	True	False	False	False	2
601182	L2	60L4626P3B	True	False	False	False	2

Table 3: Transformers with L1–L2 phase disagreement between the smart meter and machine vision methodologies.

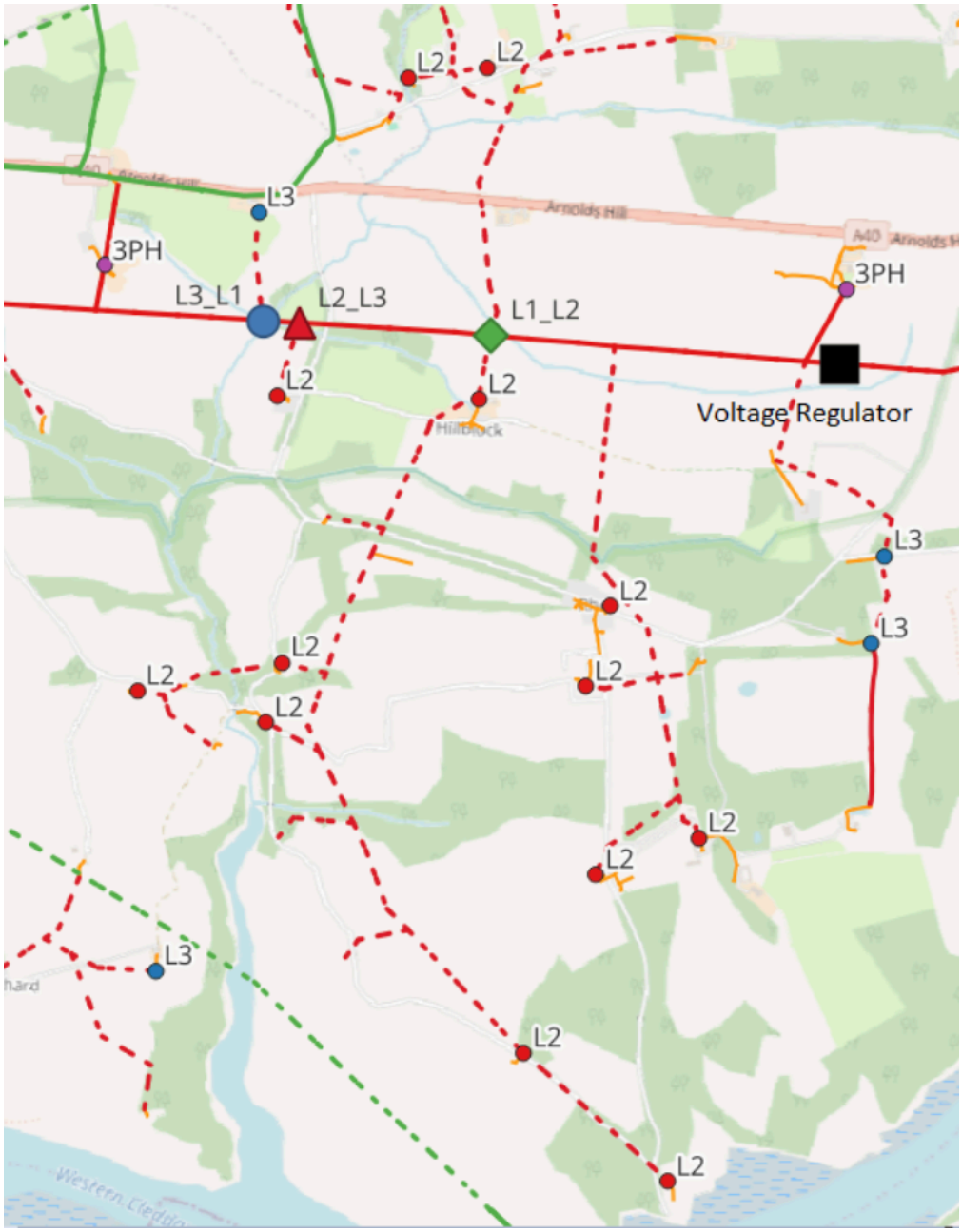


Figure 6: Cluster of L1–L2 phase mismatches on feeder 600017/0034.

Disagreements between L1 and L2 can arise from the conductor labelling convention adopted by the machine vision methodology. Phase labels are assigned assuming that the primary substation is behind the observer and that the conductors are labelled from right to left. Where this convention is not followed along the feeder, the same physical conductor pair may be assigned different L1 and L2 labels. A further possible explanation is an upstream phase transposition, which changes the electrical phase sequence while leaving the physical conductor arrangement unchanged.

To investigate this discrepancy, the machine vision results at pole 60L9P32 were reviewed. As the phase is derived from orientation of the lines the results from WP4 for pole 60L9P32 have been investigated. Figure 7 shows the derived angles used to determine the orientation of the lines in Figure 8 as per the method described in the WP4 report. In Figure 8, the helicopter positioning in relation to the pole was to the southeast with the derived corrected angle of the

main wires (TNW) aligning roughly with the upstream bearing. The results from WP4 allow for the interpretations of Figure 6 as the power source originating from the left-hand side of the image. Under the adopted conductor ordering convention, this places L1 on the lower conductor and L3 on the upper conductor, confirming that the machine vision methodology correctly identifies the single-phase spur as connected to the L1-L2 conductor pair.



Figure 7: Pole 60L9P32 results



Figure 8: Close up of the junction in image DSC01253

Although the machine vision interpretation at pole 60L9P32 is consistent with the observed conductor arrangement, the discrepancy may be explained by an upstream phase switch. The machine vision methodology assigns phase labels based on the assumed phase sequence of the three conductors along the feeder. If the conductors have been transposed at an earlier point on the network, the physical conductor pair identified at pole 60L9P32 would remain correct, but the associated phase labels would no longer correspond to the assumed sequence. For example, the conductor pair identified as L1–L2 under the assumed phase sequence could in practice correspond to L2–L3 following a phase transposition. This would explain the observed disagreement with the smart meter methodology while remaining consistent with the physical network configuration. Moreover, as shown in Figure 6, feeder 600017/0034 includes a voltage regulator. As described in WP3, voltage regulators alter downstream voltage profiles and can therefore affect voltage correlation. Consequently, all substations downstream of the regulator were excluded from the analysis. Although this avoids the direct impact of the regulator on the analysed section of the feeder, it cannot be ruled out that its operation may have some influence on voltage behaviour in the vicinity of the regulator, which could contribute to the observed discrepancies.

A comparison of the L3 classifications provides additional confidence in the results. Unlike L1 and L2, the identification of L3 is not affected by orientation ambiguity, as L3 is always associated with the outer conductor. Across the evaluated transformers, the two methodologies agreed on the L3 classification in approximately 80% of cases. Only a single

disagreement was identified, where the smart meter methodology assigned the transformer to L3, while the machine vision methodology identified the conductor pair as L1–L2.

The aerial imagery (Figure 9) clearly supports the machine vision interpretation, suggesting that the disagreement lies with the smart meter phase assignment. However, the strong correlation values shown in Table 4 indicate that this may reflect an underlying network or data issue.



Figure 9: Machine Vision Phase Assignment L1

primary feeder	substation	corr_L1	corr_L2	corr_L3	phase
417560/0041	413968	0.886	0. 898	0. 950	L3

Table 4

If it is assumed that most of the remaining disagreements are driven by orientation ambiguity - that is, by the convention used to assign phase labels from the aerial imagery, where the primary substation is assumed to be behind the observer and the conductors are labelled from right to left - then some apparent L1/L2 mismatches may simply reflect locations where this convention is not followed consistently along the feeder. This interpretation is supported by the strong agreement observed for L3 classifications, which are not affected by this convention. Excluding these orientation-related mismatches, together with the investigated low-confidence smart meter classification, the adjusted comparison shown in Table 5 provides a more representative indication of agreement between the two methodologies.

Primary Feeder	Substation Matches	Substation Total	Accuracy
417560/0041	6	7	0.857
600017/0034	11	11	1.000
770003/0001	8	9	0.889

Table 5: All Substation Comparison (adjusted after investigation)

4.3.2 Identification of Network Record Discrepancies

Figure 10 illustrates an example where the machine vision methodology identified a discrepancy between the Electric Office (EO) network records and the physical network configuration. The EO network model records this branch as a three-phase overhead line, whereas the aerial imagery clearly shows that it is a single-phase HV spur connected to the L3-L1 conductor pair. This demonstrates an additional benefit of the machine vision approach beyond phase identification, namely its ability to identify inconsistencies in existing network records. Such discrepancies can be flagged for further investigation, enabling EO data to be validated and updated where necessary, thereby improving the accuracy of network models for future planning and analysis.



Figure 10: Discrepancy between the EO network records and the physical network configuration.

4.3.3 Phase Identification in the Absence of Smart Meter Data

Figure 11 illustrates how the machine vision methodology can be used to identify the phase connection of a single-phase distribution transformer in the absence of smart meter data. The aerial imagery identifies that the single-phase HV spur is connected to the L1-L2 conductor pair of the three-phase feeder. By tracing the network connectivity from the tee point to the downstream transformer using the constructed network model, the L1-L2 phase assignment is propagated to the transformer. This demonstrates that the machine vision methodology can provide a standalone phase identification solution in areas where smart meter data is unavailable or insufficient.

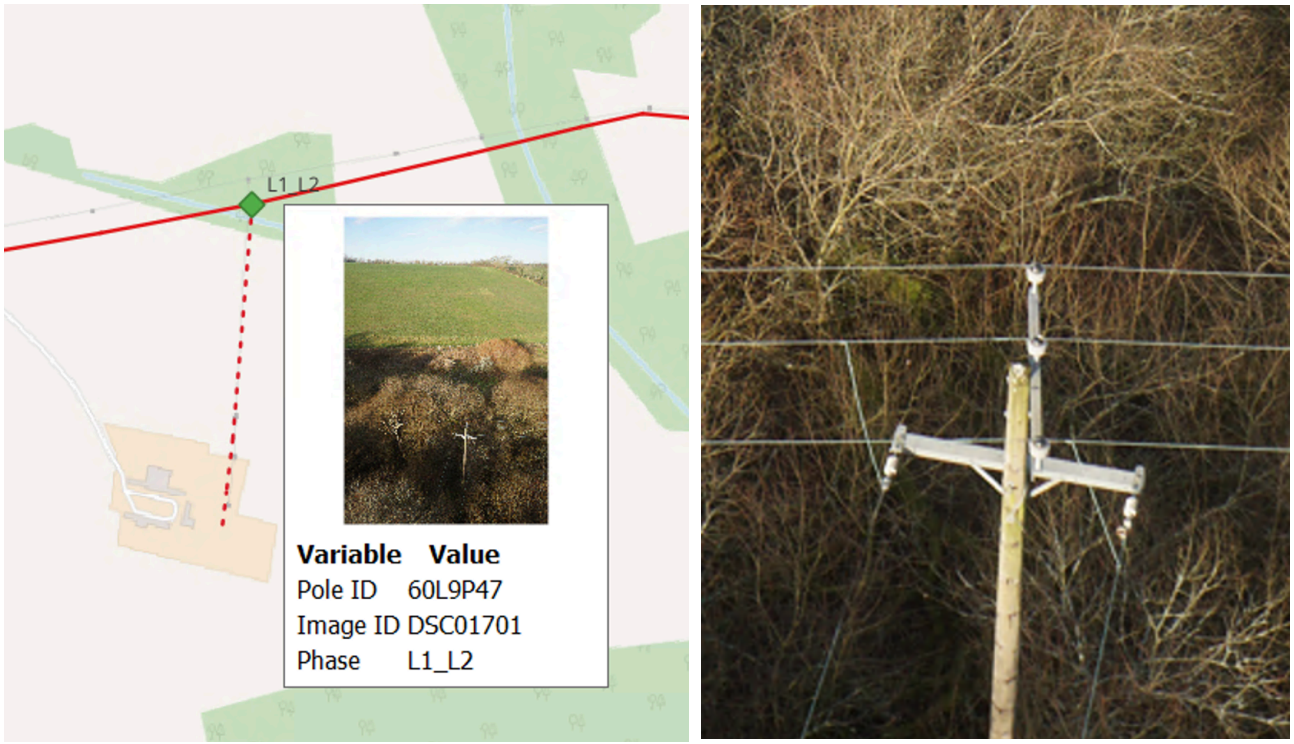


Figure 11: Machine Vision identification of conductor pairs for pole 60L9P47

This limitation is expected to be reduced over time as smart meter uptake continues to increase across the network.

4.3.4 Phase Identification in the Absence of Aerial Imagery

As discussed in WP4, the availability of suitable aerial imagery was identified as one of the principal limitations of the machine vision methodology. The existing helicopter surveys were primarily designed to support vegetation management and routine asset inspections rather than phase identification, resulting in incomplete coverage of some poles and conductor connections.

As an example, HV feeder 770003/0001 contains around 16 single-phase transformers and HV spur connections, but suitable aerial imagery was available for only around six of these locations. In locations where suitable aerial imagery is unavailable, the smart meter methodology provides an effective standalone solution for phase identification.

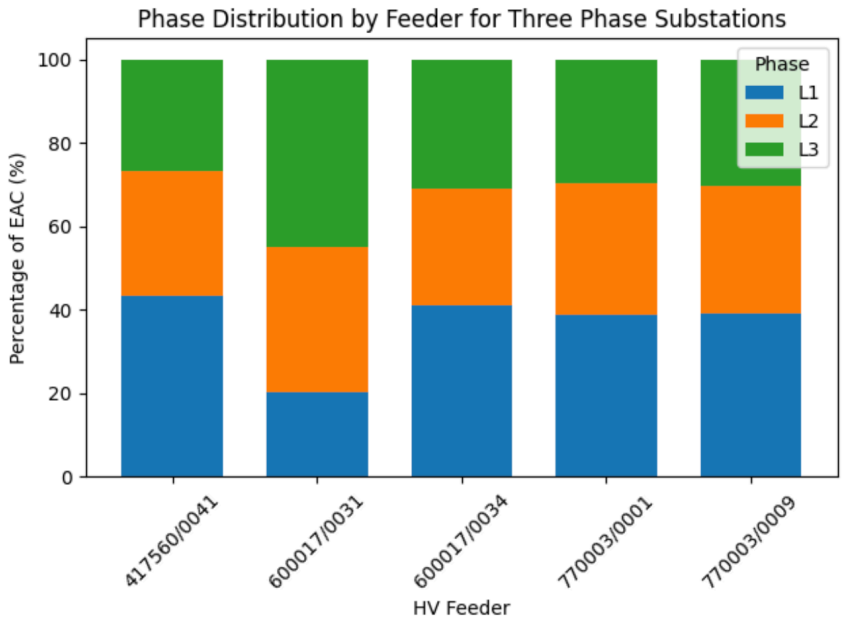
This limitation could be reduced in the future if helicopter surveys adopt higher-resolution cameras and flight plans specifically designed to support network modelling and machine vision applications. Where helicopter imagery remains unavailable or additional validation is required, targeted drone surveys could provide a practical alternative. The higher-resolution imagery obtained from drones can be used to verify the conductor configuration, identify the conductor pair supplying a single-phase HV spur, and confirm the corresponding phase connection of the downstream transformer, providing an efficient means of validating network records and phase identification results without the need for extensive site inspections.

5 Assessment of HV Feeder Phase Unbalance

This section presents an assessment of the overall phase unbalance across the analysed HV feeders based on the estimated electrical demand connected to each phase.

The analysis presented in this section extends the work undertaken in WP3 by considering the electrical demand connected to each phase rather than simply the number of customers or smart meters. The identified phase connections are combined with Estimated Annual Consumption (EAC) data to estimate the total annual load of the customers with smart meters connected to each phase. Aggregating the EAC values according to the identified phase assignments provides a more representative assessment of phase loading and enables the magnitude of phase unbalance across each HV feeder to be quantified. Although this analysis includes only customers with smart meters, there is no reason to expect that the likelihood of a customer having a smart meter, or of that meter providing usable data, is dependent on the connected phase. The resulting phase load distribution is therefore expected to be representative of the overall demand across the feeder.

The results are presented separately for three-phase distribution transformers, single-phase distribution transformers, and the combined feeder. This allows the contribution of single-phase HV spurs to the overall feeder phase unbalance to be assessed.



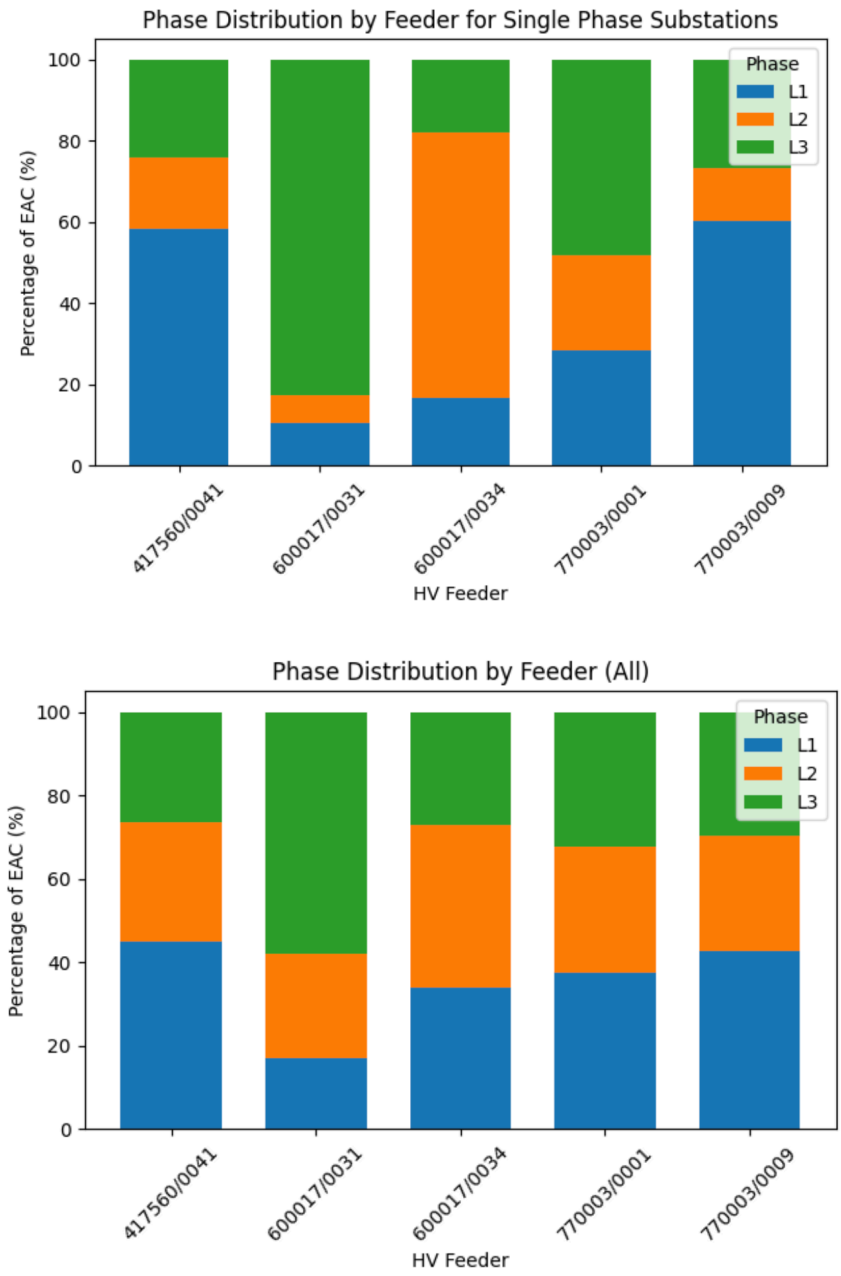


Figure 12: HV feeder phase loading using phase assignments and EAC data.

The third plot in Figure 12, showing the aggregated demand from all substations on the HV feeder, effectively represents the unbalance on the first feeder section from the primary substation. For four of the five feeders, the demand is close to being balanced in this first feeder section, though there is one with nearly 60% of demand on L3. Moving away from the primary, the level of demand aggregation reduces. For the rural feeders in our trial sample, the three-phase ground-mounted substations are mostly nearer to the primary, with single-phase substations in the more remote areas towards the ends of the feeder. In sections further from the primary, the demand is lower, mostly likely with a lower line rating to match, and the level of unbalance is typically higher. Taking an extreme case, at the remote ends of the feeder where there is only one downstream single-phase substation, 100% of the demand is on the same phase. Although, this may not necessarily be an unbalance issue.

While the previous analysis assessed the overall phase unbalance at the head of each HV feeder, the level of phase unbalance can vary significantly along the feeder as loads are connected or disconnected on individual branches. The objective of this analysis is to identify where along the feeder the greatest phase unbalance occurs, allowing sections of the network with a high concentration of load on a single phase to be identified.

To achieve this, the cumulative load was calculated progressively from the end points of the network back towards the primary substation. The analysis begins by selecting a specific one of the many end points of each HV feeder. Each end point is used as the starting point for the upstream aggregation, with the connected customer load, represented by the aggregated Estimated Annual Consumption (EAC), calculated for each phase. The network is then traced upstream towards the primary substation using the HV network topology. At each junction, the downstream loads from all connected branches are combined to produce the cumulative phase loading at that location.

Figure 13 illustrates this process for HV feeder 770003/0009, taking an end point at pole 77UUHP9A, with single-phase substation 744403 as an example. The numbering is shown as a sequence of 32 aggregation steps, from the end point back to the primary, with each step representing a junction where the aggregated demand increases, either because an additional substation is included, or because a group of substations on a side spur has joined

The corresponding stacked bar chart shows how the cumulative proportion of load connected to each phase changes at each step as additional downstream branches are incorporated.

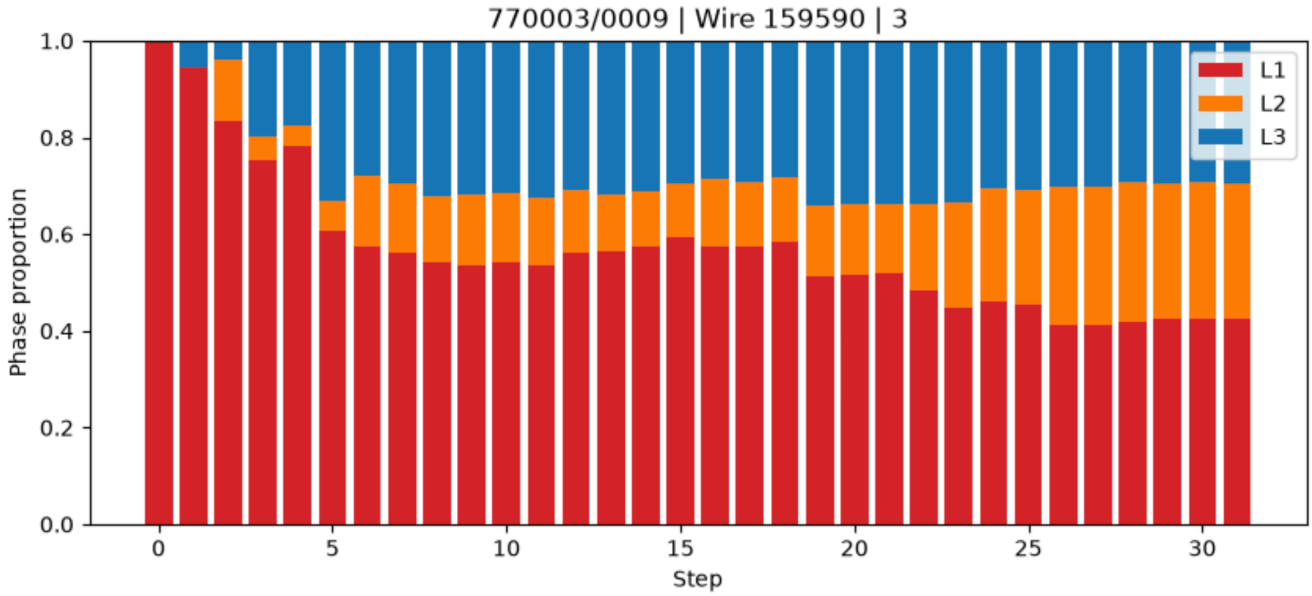


Figure 13: Workflow for calculating cumulative phase loading along an HV feeder.

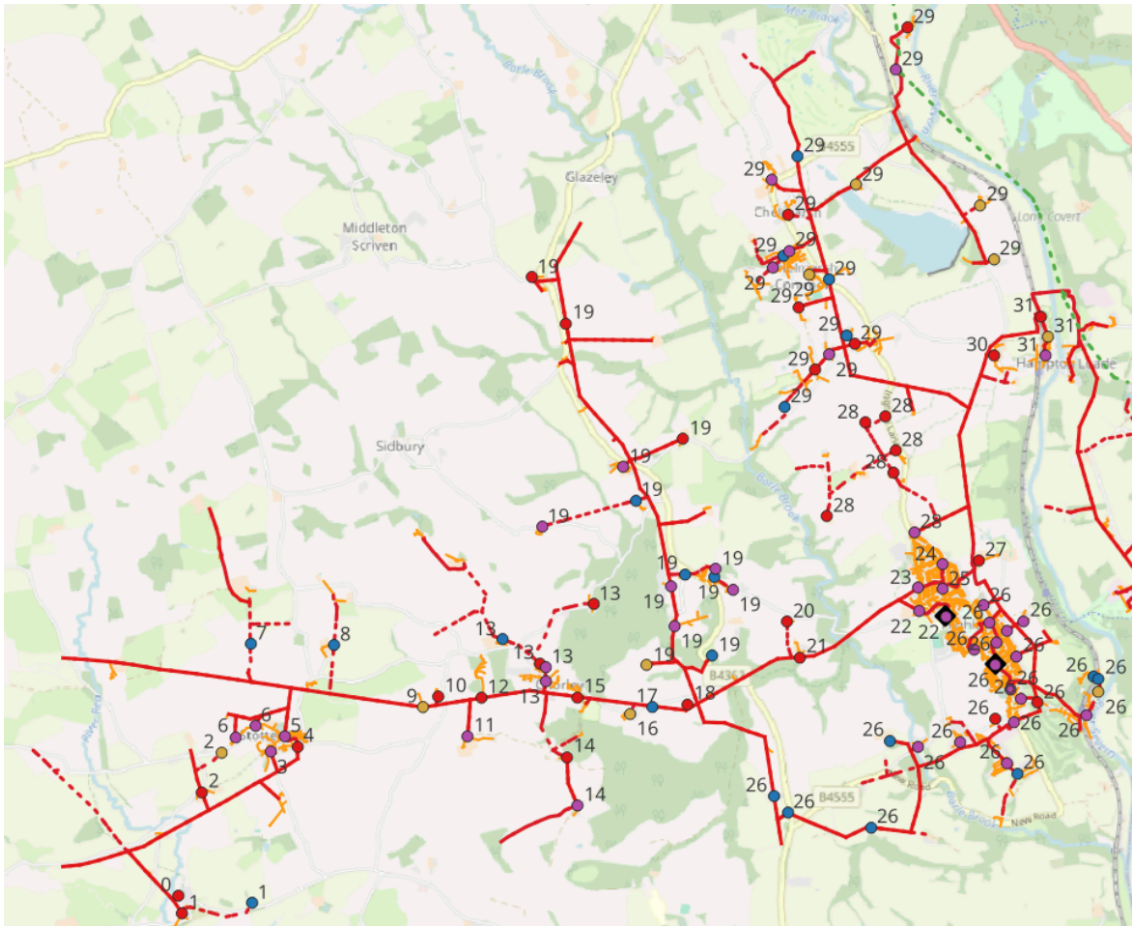


Figure 14: Network map that shows the upstream traversal sequence

It can be seen that, while the cumulative load at the primary substation (Step 31) is relatively well balanced across the three phases, the phase proportions vary considerably as the analysis moves towards the feeder end points. This indicates that individual sections of the feeder experience significantly higher phase unbalance than is apparent from the overall feeder assessment, demonstrating the value of analysing phase loading throughout the feeder rather than only at the primary substation.

Figure 15 presents a more pronounced example for HV feeder 600017/0031 with the example end point at substation 605907. Figure 16 shows the route from this selected end point to the primary substation, with the numbers showing the substations on side spurs that are added at each of the 20 aggregation steps. Unlike the previous feeder, where the phase loading becomes progressively more balanced towards the primary substation, this feeder exhibits a significant phase unbalance throughout almost its entire length. As the cumulative load is traced upstream, the majority of the demand remains connected to phase L3, while the contributions from phases L1 and L2 remain comparatively small. Consequently, even at the head of the feeder, the overall load distribution remains highly unbalanced.

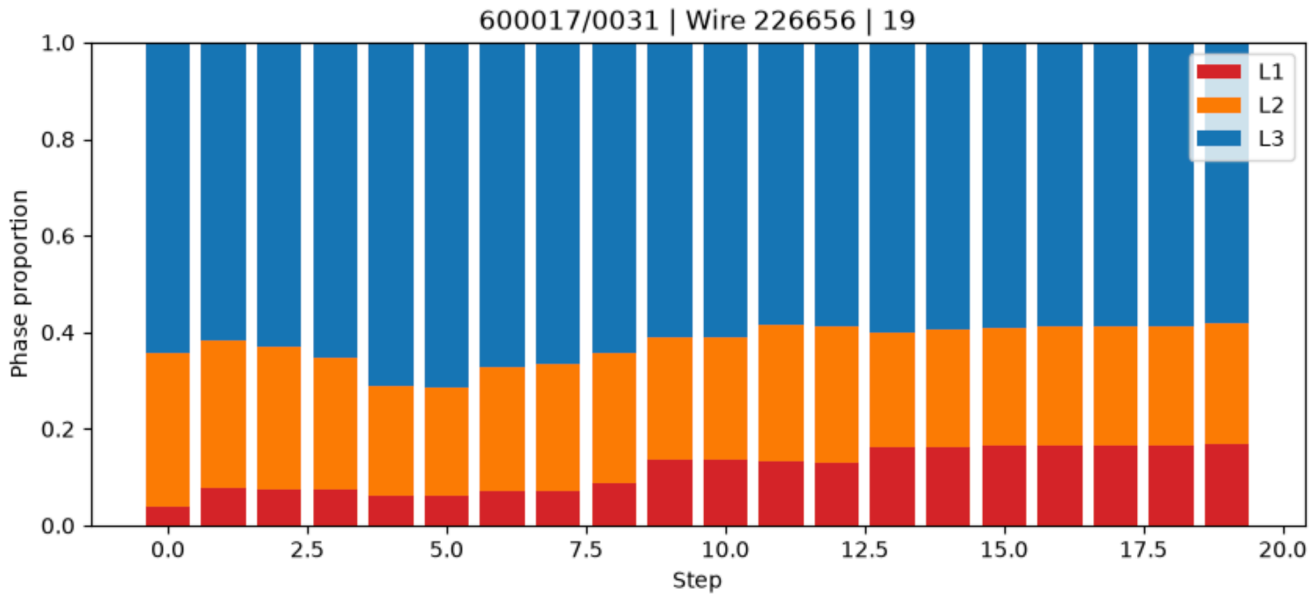


Figure 15: Upstream cumulative phase loading for HV feeder 600017/0031, illustrating sustained phase unbalance along the feeder.

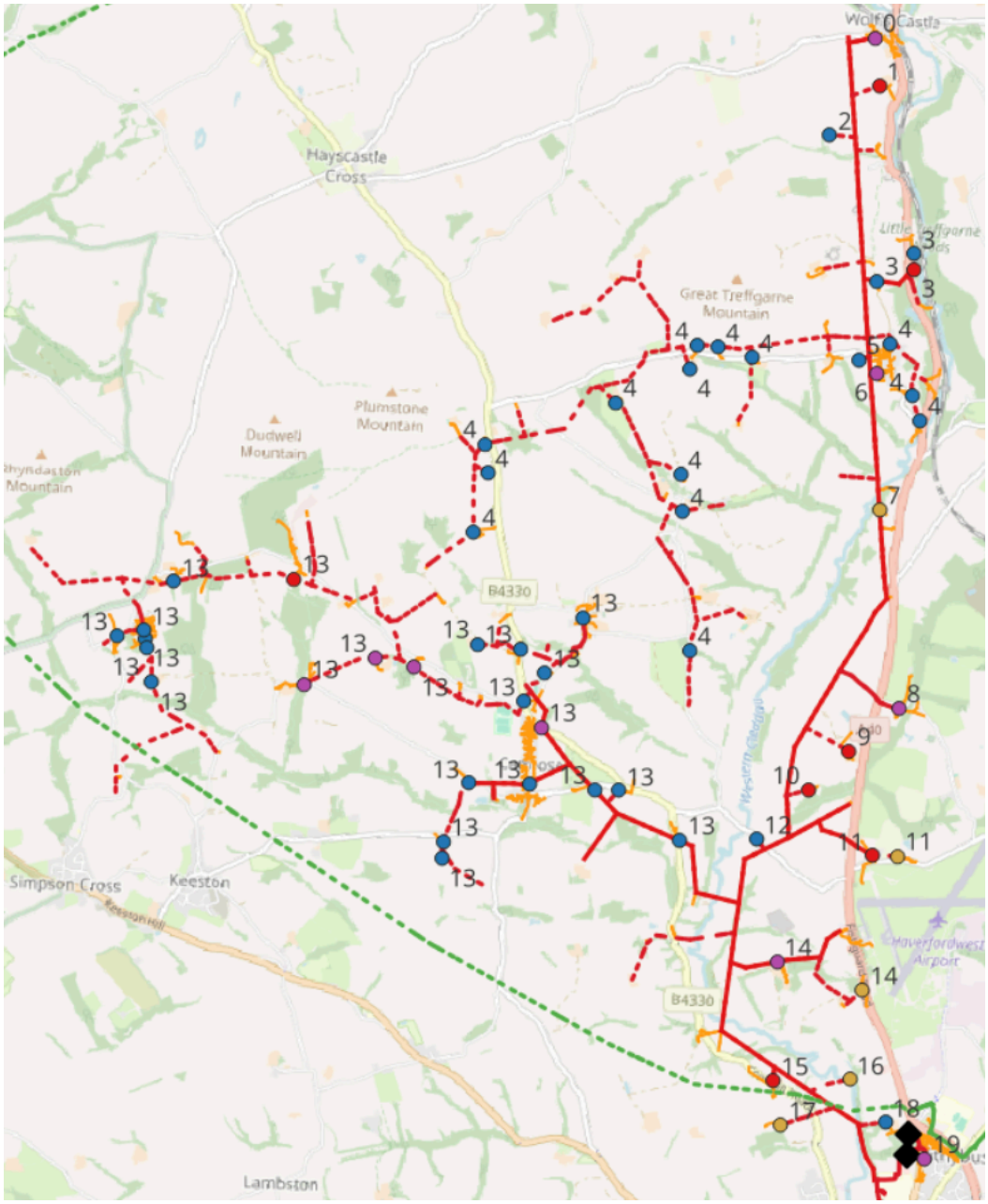


Figure 16: Network map that shows the upstream traversal sequence for HV feeder 600017/0031

This analysis demonstrates the value of assessing phase loading throughout the feeder rather than only at the primary substation. In the more remote sections of the feeder, demand will be lower, but the unbalance is typically higher and could represent a greater bottleneck relative to the line rating, than nearer to the primary where demand is greater but is mostly more balanced.

6 Business Benefits and Capacity Release Opportunities

The strongest business benefit is the conversion of phase-identification evidence into a repeatable capacity-release process. The value should be measured as usable headroom identified or released on constrained

rural sections, supported by the number of practical interventions, record corrections, and avoided or deferred reinforcement decisions generated by the pilot.

The pilot should not rely on a single headline feeder metric. It should produce a ranked portfolio of local opportunities, because rural capacity constraints often sit on specific spurs, long branches, or groups of single-phase transformers. This also makes the output more actionable for field and planning teams.

6.1 Benefit measures for the pilot

- Estimated kVA or MVA headroom released, or made visible, by feeder section and intervention type.
- Number of high-confidence phase assignments created for single-phase transformers and spurs.
- Number of actionable phase-balancing candidates, ranked by expected capacity benefit and confidence.
- Number of EO record discrepancies identified, validated, and ready for correction.
- Reduction in manual survey effort for connection studies and network planning queries.
- Decision-cycle improvement for rural connection enquiries where phase headroom is the limiting factor.

7 Data Requirements

The data requirements are framed around the production workflow and the capacity-release use case. The proposed minimum viable pilot dataset is:

- EO network topology (network model) for selected rural feeders, including poles, tee points, single-phase spurs, transformers, switches, and upstream/downstream connectivity.
- Asset identifiers for pole, transformer, conductor, feeder, and customer/load records.
- Smart-meter voltage profiles, as used in WP3 for phase correlation outputs, and confidence/quality indicators.
- EAC, peak-demand proxy, or other agreed load measure linked to transformers and customer groups.
- Aerial or drone imagery for selected intersection poles, with image where available.
- Known network changes, phase swaps, planned reinforcement, and exception records that may affect phase interpretation.
- A targeted validation sample for high-value or low-confidence sites.

8 Proposed Approach

8.1 Approach

Use combination of the 2 approaches outlined e.g. smart meter-based phase determination and Machine Vision based conductor mapping with a consolidated network data model to calculate the phase balance over at least 10 to 15% of the overall network.

Images for the Machine Vision part should be ideally sourced from drone images taken for each of the network intersection poles and transformers. With several images taken for each pole from various viewpoints.

The Machine Vision line phase data and the smart-meter phase correlation data can be used to cross check the output of each approach.

The approach should focus on single-phase branches downstream of tee points and should convert phase identification into branch-level capacity-release opportunities.

- Select feeder cohort: choose rural feeders with high single-phase spur density, known connection pressure, or visible unbalance in existing WP3/WP4 results.
- Build the network model: join EO assets, pole connectivity, transformer associations, and downstream branch relationships.
- Integrate phase evidence: combine WP3 smart-meter assignments with WP4 conductor-pair observations and propagate evidence through the graph.
- Score confidence: record agreement, disagreement, degree of separation, data quality, imagery coverage, and smart-meter coverage.
- Calculate branch loading: combine phase assignment with EAC or agreed demand proxies to estimate phase loading and headroom along each branch.
- Rank interventions: identify phase swaps, record corrections, targeted validation, and potential reinforcement options by benefit, confidence, and delivery complexity.
- Package for production: define refresh rules, ownership, audit trail, and the process for moving validated corrections into business systems.

9 Proposed Outcome

The proposed outcome is a pilot-ready evidence package that can be used by planning, connections, asset data, and field teams to release or protect rural network capacity.

- Branch-level phase connectivity model with traceable evidence from smart meters, imagery, and network topology.
- Capacity-release dashboard showing phase loading, local headroom, confidence, and intervention candidates.
- Prioritised intervention register covering phase balancing, targeted validation, record correction, and targeted reinforcement candidates.

- Network discrepancy log that separates likely data issues from potential upstream phase transpositions or smart-meter uncertainty.
- Production handover pack covering governance, refresh cadence, exception handling, and acceptance criteria.

Planned delivery:

- Visualization that shows how the phases are distributed
- Database that is maintainable with a strategy for records to be modified as changes are made across the network
- Network diagnostics that indicate problem areas withing the network

9.1 Visualization

The visualisation should present a map-first view of the selected feeder cohort. Each branch should show assigned phase, confidence, connected load, degree of separation from known evidence, and intervention status. Users should be able to filter by rural feeder, confidence band, phase unbalance, record discrepancy, and estimated capacity release.

A companion chart should show how phase loading accumulates upstream from each endpoint to the primary substation, so planners can see whether the constraint is localised to a branch or persists across the feeder.

9.2 Expected data structures as output

Expected pilot outputs should be structured so they can be refreshed and governed:

- Feeder graph table: node ID, upstream node, downstream node, asset type, feeder, branch, coordinates, and connectivity confidence.
- Phase evidence table: asset ID, method source, assigned phase or conductor pair, confidence, timestamp, and evidence reference.
- Load and headroom table: asset or branch ID, phase load, cumulative upstream load, limiting phase, estimated headroom, and assumptions.
- Opportunity register: location, intervention type, expected capacity benefit, confidence, validation need, delivery owner, and status.
- Record discrepancy register: EO record, observed configuration, evidence source, severity, recommended correction, and approval status.



