

HV Pilot

NIA Closedown Report

May 2025 – August 2026

Electricity Distribution

nationalgrid

Version Control

Issue	Date
V0_1	7th August 2026
V0_2	15th September 2026
V1	16th Sepytember 2026

Publication Control

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1. Executive Summary

HV Pilot was a Network Innovation Allowance (NIA) project with an approved budget of £901,477 and a planned duration of 16 months. The project commenced in April 2025 and was delivered in line with both the approved budget and project timescale.

The project was established to investigate whether the phase connectivity of single-phase transformers connected to rural high-voltage (HV) networks could be identified using existing operational datasets. This is needed as existing phase connectivity information in transformer asset records are largely incomplete and not considered to be reliable. Improved visibility of phase allocation has the potential to enhance network modelling, improve understanding of phase unbalance and support more effective utilisation of existing network capacity.

Two complementary approaches were assessed. Smart meter and network monitoring data were used to identify phase allocation through analysis of voltage behaviour, whilst machine vision techniques were developed to derive physical connectivity information from aerial imagery and LiDAR datasets.

The project assessed seven HV feeders containing approximately 970 secondary substations and 8,692 customers. Smart meter-based methodologies achieved phase identification accuracies of up to 96.9% and correctly identified more than 91% of single-phase transformers. The machine vision assessment reviewed more than 10,000 aerial images, identified 95 pole locations and reconstructed 52 distinct network connections.

A dedicated analytical environment was developed to integrate smart meter data, monitoring information, network records, aerial imagery and LiDAR datasets. This enabled the outputs from the smart meter and machine vision methodologies to be compared within a common network model and supported the development of an integrated connectivity assessment approach.

Comparison of the smart meter and machine vision outputs showed that the two methodologies provide complementary sources of evidence. Investigation of apparent discrepancies identified a number of factors affecting interpretation of the results, including conductor orientation assumptions, voltage regulators and confidence levels. Bringing the different sources of evidence together increased confidence in the resulting connectivity assessments and helped identify locations where further investigation may be beneficial.

The work also identified benefits beyond phase identification. The methodologies were shown to support network record validation, improve understanding of network connectivity and provide greater visibility of phase utilisation within rural HV networks. Analysis of phase loading showed that feeder-level assessments can mask significant localised phase unbalance and highlighted opportunities for future work relating to phase balancing and network capacity utilisation.

HV Pilot increased the maturity of smart meter analytics, machine vision and integrated connectivity assessment methodologies through demonstration on representative rural HV feeders using operational datasets. The outcomes are considered consistent with progression from TRL4 to TRL6, with further validation required before wider deployment could be considered.

Overall, the project met its objectives, demonstrated practical approaches for improving visibility of HV phase allocation and connectivity, and established a foundation for future work relating to network visibility, network record validation, phase balancing and capacity assessment.

2. Project Background

National Grid Electricity Distribution (NGED) operates an extensive high-voltage (HV) distribution network comprising approximately 220,000 km of overhead lines and underground cables and around 185,000 substations across its licence areas. Many rural areas are supplied via overhead line networks incorporating a mixture of three-phase and single-phase distribution substations.

Historically, limited visibility of phase allocation has had relatively little impact on network operation. However, the increasing uptake of low-carbon technologies, including electric vehicles, heat pumps and solar photovoltaic (PV) systems, is placing greater demands on network capacity and increasing the need for more detailed and accurate network information.

Without a clear understanding of phase connectivity, it is difficult to accurately model how load is distributed across the individual phases of an HV feeder. This reduces confidence in network studies, limits understanding of phase unbalance and makes it more difficult to identify spare capacity or assess the impact of new connections. In rural networks, these challenges are often compounded by the presence of single-phase transformers supplied from two-wire HV spur connections, where phase information may be incomplete or unavailable.

Existing methods for determining phase allocation typically rely on engineering records, site visits and field surveys. Whilst effective, these approaches can be time-consuming and resource intensive, particularly where transformers are located on pole-mounted infrastructure in remote locations.

At the same time, the electricity industry is generating increasing volumes of digital data through smart meters, network monitoring systems, aerial surveys and geospatial datasets. These data sources provide an opportunity to improve understanding of network connectivity and phase allocation without relying solely on traditional survey methods.

HV Pilot was established to investigate whether these existing data sources and associated analytical techniques could be used to identify the phase connectivity of single-phase transformers connected to rural HV networks. The project sought to improve network visibility, address gaps in connectivity information and determine whether improved understanding of phase allocation could support more accurate network modelling and better utilisation of existing network capacity in the future.

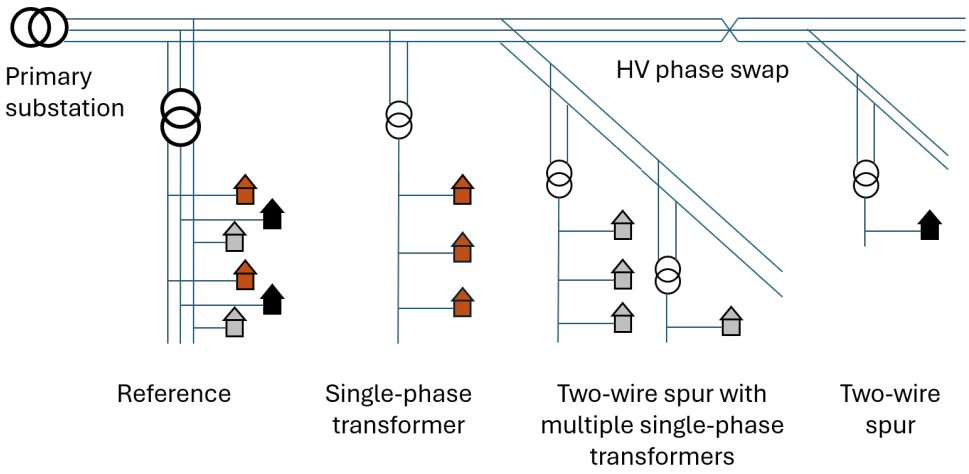


Figure 1: Example HV feeder with single-phase distribution transformers and single-phase spurs

3. Scope and Objectives

The scope of HV Pilot was to investigate whether existing operational datasets and analytical techniques could be used to identify the phase connectivity of single-phase transformers connected to rural HV networks.

The project focused on four principal areas:

1. Identification of HV feeder phase allocation and associated single-phase transformer phase connections.
2. Integration and management of data from smart meters, monitoring systems, aerial imagery and existing network records to improve visibility of network connectivity.
3. Application of smart meter analytics and machine vision techniques to identify phase allocation and assess connectivity relationships.
4. Development of the data architecture and analytical environment required to support data collection, integration, analysis and interpretation.

The project included the assessment of smart meter data, network monitoring information, aerial imagery, LiDAR datasets and existing network records. These datasets were used to develop and evaluate methodologies for HV phase identification and connectivity assessment using representative rural HV networks.

The project also sought to understand how improved visibility of phase allocation and network connectivity could support wider network planning and operational activities. Potential benefits identified at project registration included:

- More accurate modelling of unbalanced three-phase networks.
- Reduced energy losses through improved phase selection for new connections.
- Improved phase balancing and reduced network impacts associated with phase unbalance.
- Increased capacity for low-carbon technologies, including heat pumps, electric vehicle chargers and photovoltaic systems.
- More targeted deployment of network monitoring.
- Reduced reliance on manual connectivity surveys.
- Earlier identification and correction of network data issues.
- Improved use of network information for planning and operational decision-making.

This scope was delivered through five work packages covering trial area selection, data architecture, smart meter analytics, machine vision and integrated connectivity assessment.

Table 3-1: Status of project objectives

Objective	Status
Explore solutions for determining HV phasing.	✓
Integrate and manage data from multiple sources.	✓
Develop algorithms using smart meter data to identify HV phase allocation.	✓
Identify a methodology to address HV connectivity gaps.	✓
Leverage new technologies, including smart meters, monitoring systems and aerial imagery.	✓
Apply the developed algorithms to real-world network scenarios.	✓
Assess performance and identify factors influencing results.	✓
Capture learning and disseminate findings.	✓

4. Success Criteria

The project was considered successful if it:

Table 4-1: Status of project objectives

Success Criteria	Status
Successfully assessed and evaluated network data to identify the project sample areas.	✓
Analysed helicopter images to determine their usability and relevance for applying machine learning techniques.	✓
Compiled comprehensive reports on network data assessments, visual data analysis, and the outcomes of area selection.	✓
Identified and integrated suitable hardware, software, and interfaces to facilitate efficient data collection, processing, and analysis.	✓
Thoroughly tested and evaluated algorithms, to ensure they met the specified use case requirements.	✓
Produced detailed reports on selected algorithms, the development and optimisation of methods, and the learning outcomes from applying these algorithms.	✓
Developed a robust machine vision system for phase identification, complete with thorough methodologies, techniques, and performance analyses.	✓
Clearly summarised project findings and construction of a compelling business case and successfully developed a beta application.	✓

5. Details of the Work Carried Out

The project was delivered through a series of work packages covering trial area selection, assessment of available datasets, development of a supporting analytical environment, smart meter-based phase identification, machine vision assessment and the integration of outputs from the different methodologies.

A range of operational datasets was used throughout the project, including network records, smart meter measurements, network monitoring data, aerial imagery and LiDAR datasets. These datasets were assessed, integrated and analysed to investigate whether HV phase allocation and network connectivity could be identified using existing sources of information.

The project combined expertise from National Grid Electricity Distribution (NGED), CGI and Loughborough University. Each work package focused on a different aspect of the connectivity challenge, with the overall objective of determining whether multiple independent sources of evidence could be used to improve visibility of HV phase allocation and network connectivity.



Figure 2: HV Pilot Work Package Structure

The following sections summarise the activities undertaken within each work package and the methodologies developed during the project.

5.1 Work Package 1: Network Data Assessment and Trial Area Selection

WP1 focused on identifying a suitable trial area and assessing the availability of the datasets required to support the subsequent smart meter and machine vision workstreams.

The work commenced with a review of NGED network data to identify HV feeders with characteristics suitable for phase identification and connectivity assessment. This included consideration of feeder topology, monitoring coverage, smart meter penetration, network records and the availability of aerial imagery. The selection of HV feeders for the study was biased towards those with unusually long line lengths and serving a higher than average number of single-phase transformers. These feeders were considered to be at greater risk of capacity constraints, and were thought to be more challenging for the phase identification methods.

Network monitoring inventories were reviewed to identify feeders containing substation monitoring equipment that could support the smart meter-based methodologies. Feeders with substation monitoring were prioritised in the sample study to support validation of the results, and to assess how phase identification could be improved where this data is available, but the methods developed do not depend on this. Existing network records and geospatial information were also assessed to understand feeder characteristics and support subsequent feeder selection activities.

In parallel, a visual assessment of available helicopter survey imagery was undertaken to determine whether the imagery was suitable for machine vision applications. This included review of image quality, conductor visibility, pole visibility and network coverage. The assessment also considered available LiDAR datasets and associated metadata required to support image interpretation and network reconstruction.

The outputs from the network and visual assessments were used to define a set of selection criteria for identifying candidate feeders. These criteria considered:

- availability of smart meter data;
- availability of LV monitoring data;
- feeder topology and network characteristics;
- availability of supporting network records; and
- presence of single-phase transformer connections and spur networks.

Application of these criteria produced a long-list of candidate feeders for which data was available to support the smart meter method. These feeders were then assessed to determine whether usable aerial survey data was also available. This review considered both the availability and the quality of the images. Based on initial expectations of the performance of the machine vision algorithms, only seven feeders were expected to be viable for the project study. However, subsequent experience suggests that good results might have been achieved for a greater number of feeders as the machine vision has been found to work well even on images that are difficult for human interpretation.

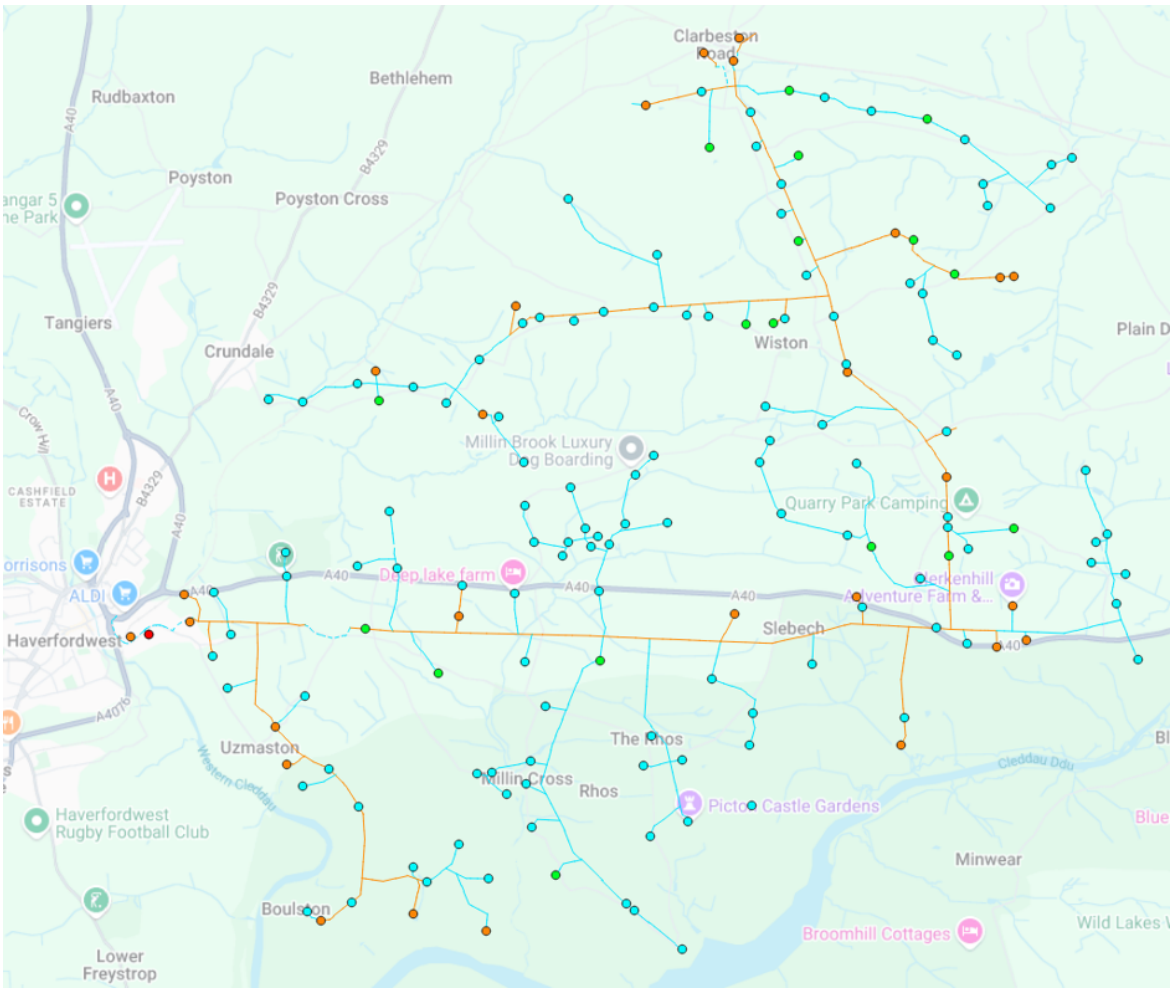


Figure 3: Example rural overhead HV feeder

The outputs of WP1 provided the trial area used throughout the project and established the datasets that would subsequently be used within the smart meter analytics, machine vision and integrated assessment activities.

Key Deliverables:

- WP1 D1 Network Data Assessment Report
- WP1 D2 Visual Data Assessment Report
- WP1 D3 Area Selection Report

5.2 Work Package 2: Data Architecture and Analytical Environment

WP2 focused on developing the data architecture and analytical environment required to support the smart meter and machine vision activities undertaken later in the project.

An early activity was the identification and review of the datasets required to support connectivity assessment. These included smart meter measurements, LV monitoring data, network records, aerial imagery, LiDAR datasets and geospatial information. As these datasets were held within different systems and formats, a common model was required to enable them to be used together.

The work therefore focused on establishing a data architecture capable of ingesting, storing, transforming and presenting information from multiple sources in a consistent manner. The solution was developed using Microsoft Azure technologies and incorporated Azure SQL databases, Azure Databricks processing environments, data pipelines and visualisation tools.

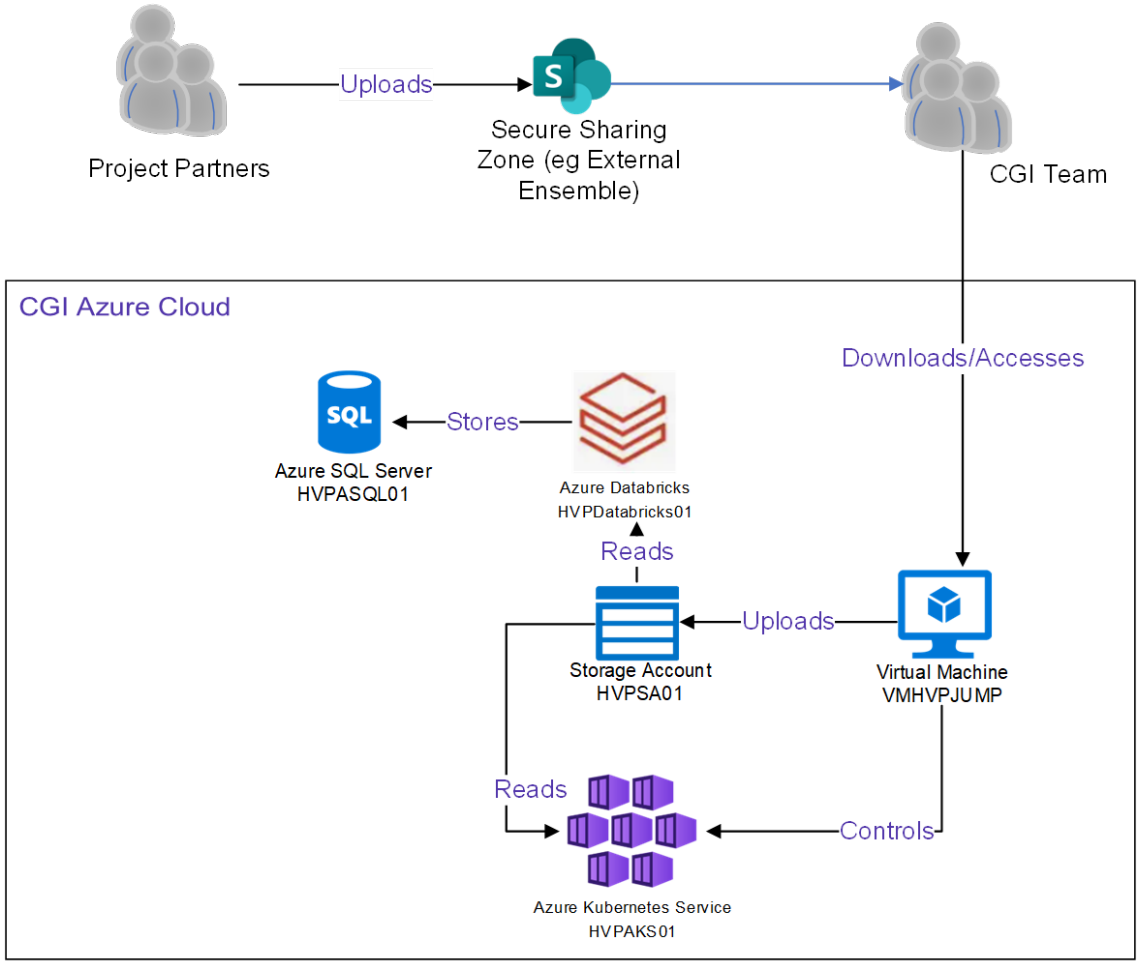


Figure 4: Simplified Architecture Diagram for HV Pilot

The architecture was structured around a series of data layers which supported:

- ingestion of source data;
- data validation and cleansing;
- transformation and integration activities;
- creation of analytical datasets; and
- presentation of outputs and visualisations.

A key activity within WP2 was the development of processes to connect information held across multiple operational systems. This included establishing relationships between customers, smart meters, monitoring devices, substations, feeders and network assets, enabling datasets to be linked and analysed together.

The work also included the development of data quality checks and validation processes to identify incomplete, inconsistent or unsuitable records before analysis was undertaken. These activities informed subsequent smart meter and machine vision assessments and helped improve confidence in the analytical outputs generated by the project.

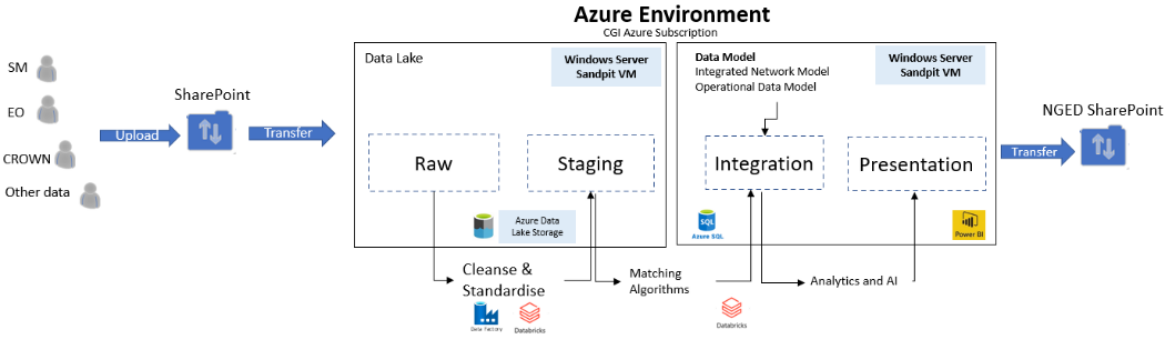


Figure 5: Data Ingestion and Processing Architecture

A graph-based network model was also developed to represent the relationships between feeders, poles, substations, transformers and customers. This model formed an important component of the analytical environment and was subsequently used to support the integrated assessment activities undertaken in WP5.

The architecture was designed to support the storage and processing of large volumes of smart meter and monitoring data, whilst also providing a mechanism for incorporating imagery, LiDAR and network record information into a common environment.

Reporting and visualisation capabilities were developed using Power BI, allowing project outputs, network structures and connectivity relationships to be explored more effectively.

The outputs of WP2 provided the analytical environment used throughout the remainder of the project and established the data structures required to support smart meter analytics, machine vision assessment and integrated connectivity analysis.

Key Deliverables:

- WP2 D1 Data Architecture and DataStore Overview v2.0
- Data integration and processing environment
- Graph-based network model
- Visualisation and reporting environment

5.3 Work Package 3: Smart Meter-Based Phase Identification

WP3 focused on the development and assessment of methodologies capable of identifying HV phase allocation using smart meter voltage measurements. Building on learning from the Smart Meter Innovations and Testing Network (SMITN) project, the work investigated whether techniques previously applied to LV phase identification could be extended to identify the phase connectivity of single-phase transformers connected to rural HV networks.

The work showed that smart meter voltage data contains sufficient information to identify HV phase allocation across real distribution networks. The methodologies developed were able to use relationships between voltage measurements to infer connectivity information using data that is already becoming increasingly available across the network.

The selected trial feeders contained approximately 8,692 customers with smart meter penetration of around 53%. Approximately 81% of smart meters returned usable half-hourly voltage measurements during the project, though only 43% of meters were successfully re-configured and provided 10-minute voltage data.

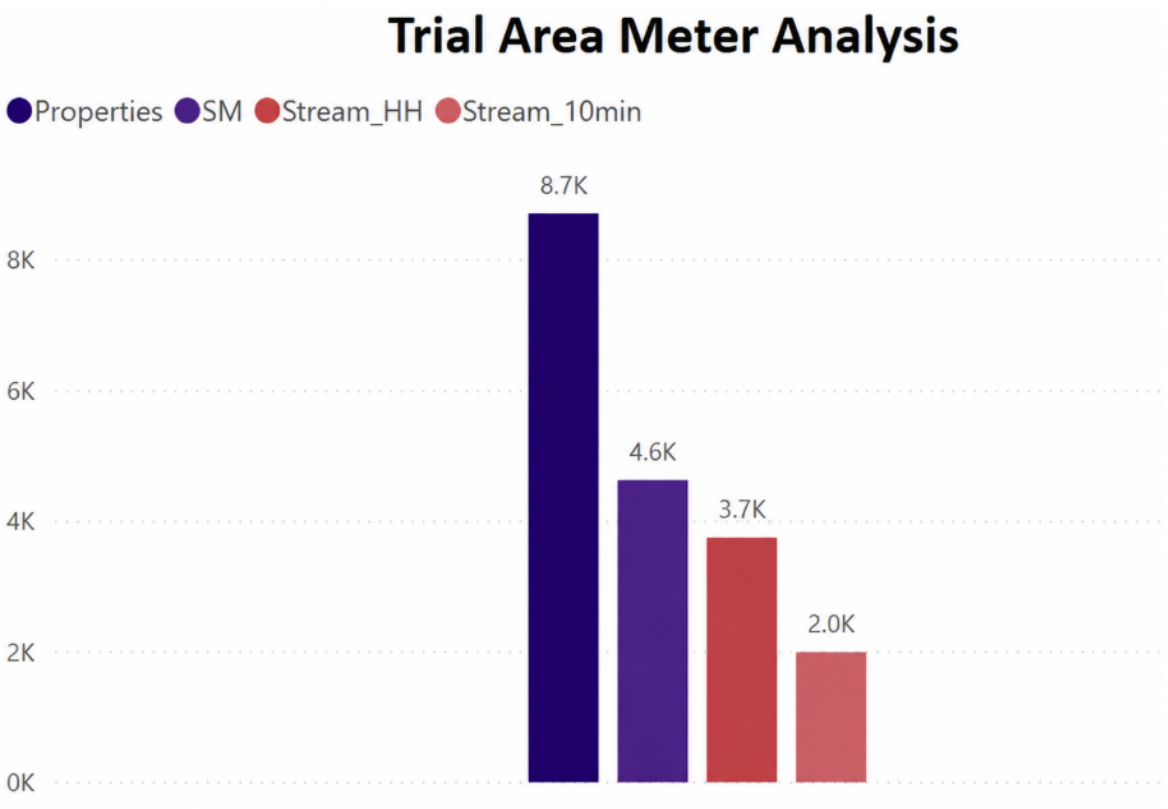


Figure 6: Smart meter coverage in trial feeders

Depending on feeder configuration and customer distribution, sufficient data existed to support direct phase identification for approximately 48% to 60% of substations.

Data Preparation, Validation and Confidence

The first stage of the work involved preparing and validating the smart meter datasets used throughout the analysis. Activities included reviewing smart meter allocations, assessing data quality, synchronising measurement timestamps, removing anomalous devices and identifying suitable datasets for analysis.

A particular challenge was that some smart meters provide voltage data averaged over periods that begin at different times. For example, half-hourly measurements may not start at 00 and 30 minutes after the hour. As the phase identification method relies on comparing simultaneous voltage variations between smart meters, these timing offsets can reduce the accuracy of the correlation results. Identifying and addressing timestamp misalignment was therefore an important part of the data preparation process.

The analysis method included:

- validating smart meter allocations, ensuring that the analysis only considered smart meters that were actually connected at the substation, as connection records can sometimes be in error;
- identifying and correcting timestamp issues;
- synchronising measurement data;
- removing voltage outliers;
- assessing data completeness; and
- developing confidence measures for individual phase assignments.

Devices with weak correlation characteristics reduced classification accuracy and clustering stability, while timestamp issues could materially affect phase assignment results.

Two measures of confidence were developed. Firstly, where a substation was confirmed to be single-phase, a higher proportion of smart meters with the same phase identification increased confidence in the results. Secondly, confidence was increased when the phase identification using successive data time periods giving the same result.

Development and Assessment of Multiple Analytical Approaches

Several analytical approaches were subsequently developed and assessed. These approaches were designed to operate under different network and data availability scenarios and included:

- Approach A - Correlation against monitored reference substations.
- Approach B - Clustering of smart meter voltage behaviour.
- Approach C - Sequential phase identification using reference substations and reference smart meters.

Results from these three approaches were compared to determine the conditions under which each approach was most effective.

Approach A: Correlation with Monitored Reference Substations

Approach A used monitored three-phase substations as reference points and compared smart meter voltage measurements against monitored phase voltages to identify likely phase relationships.

The methodology achieved approximately 89% agreement with existing CROWN phase records, with phase identification accuracy exceeding 90% and reaching 94.3% on some feeders.

Performance was assessed across different analysis windows, with results remaining generally consistent over time. This provided confidence that the methodology was identifying underlying electrical relationships rather than patterns associated with a particular operating condition or analysis period.

The work demonstrated that existing monitoring infrastructure can provide an effective reference for phase identification and that voltage phase variations can be used to infer connectivity without additional field investigation.

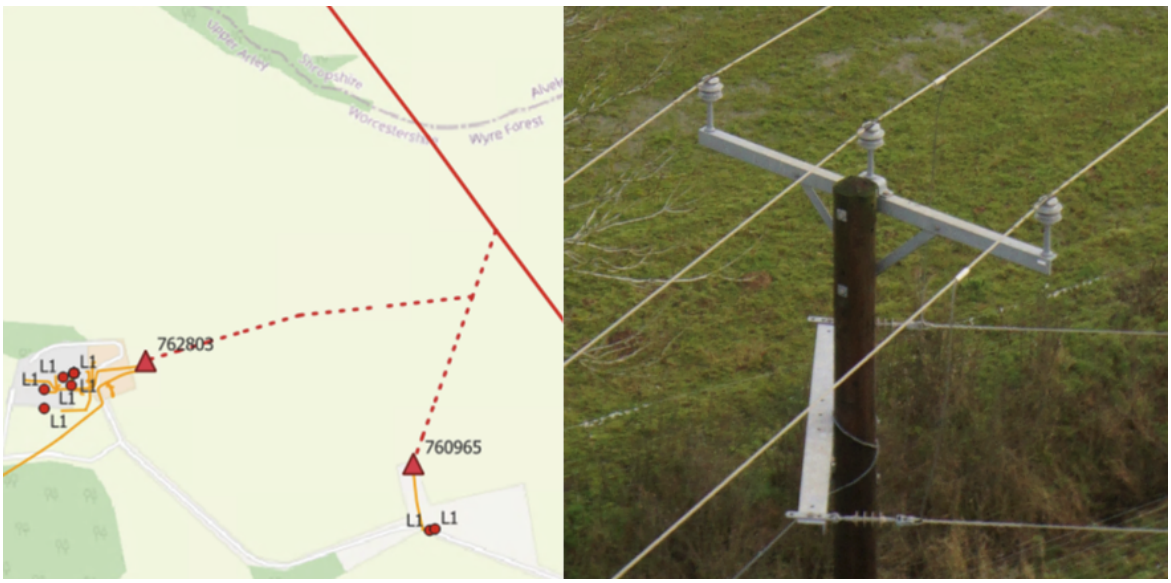


Figure 7: Correlation-based phase identification validated by aerial imagery for a single-phase branch

Approach B: Feeder-Level Clustering

Approach B investigated whether phase allocation could be identified directly from groups of smart meter voltage measurements without relying on monitored reference substations. These methods are needed as most substations do not have monitoring installed.

The methodology used clustering techniques to group customers exhibiting similar voltage behaviour, demonstrating that phase information could still be extracted where monitoring infrastructure was unavailable.

In Approach B, all customers on the HV feeder were clustered, regardless of their distribution substation connection, forming one cluster for each phase. Ideally, all customers connected to the same single-phase substation would be found to be in the same cluster.

Performance varied depending on feeder characteristics and data quality, with accuracies ranging from approximately 60% to 94% and Rand Index values between 0.65 and 0.93.

The approach was found to be particularly sensitive to:

- voltage regulator operation;
- outlier measurements;
- low smart meter density;
- data quality issues; and
- feeder-specific operating characteristics.

Although performance was generally lower than the reference-based approaches, the methodology provided an independent means of assessing phase allocation and remained useful where monitoring infrastructure was unavailable.



Figure 8: HV feeder-level clustering results for a single-phase distribution transformer showing consistent phase assignment

Approach C: Sequential Phase Identification

Approach C was developed to support situations where monitored reference substations were unavailable. The methodology established phase relationships using selected reference substations and reference smart meters before progressively identifying phase allocation across the feeder.

Appoach C therefore differs from Approach B as the clustering was applied first for the reference substation, providing a proxy for substation monitoring, and then the smart meters from other substations were associated with the reference substation clusters.

Performance was generally strong across the selected feeders. The methodology achieved approximately 86% agreement with existing network records, with typical accuracies between 85% and 95%. Maximum performance reached 96.9% accuracy, with Rand Index values of up to 0.959.

More than 91% of single-phase transformers were correctly identified using this approach.

The analysis also demonstrated that the selection of suitable reference substations had a significant influence on performance. The strongest results were obtained where reference substations contained sufficient smart meter populations and exhibited strong correlation characteristics.

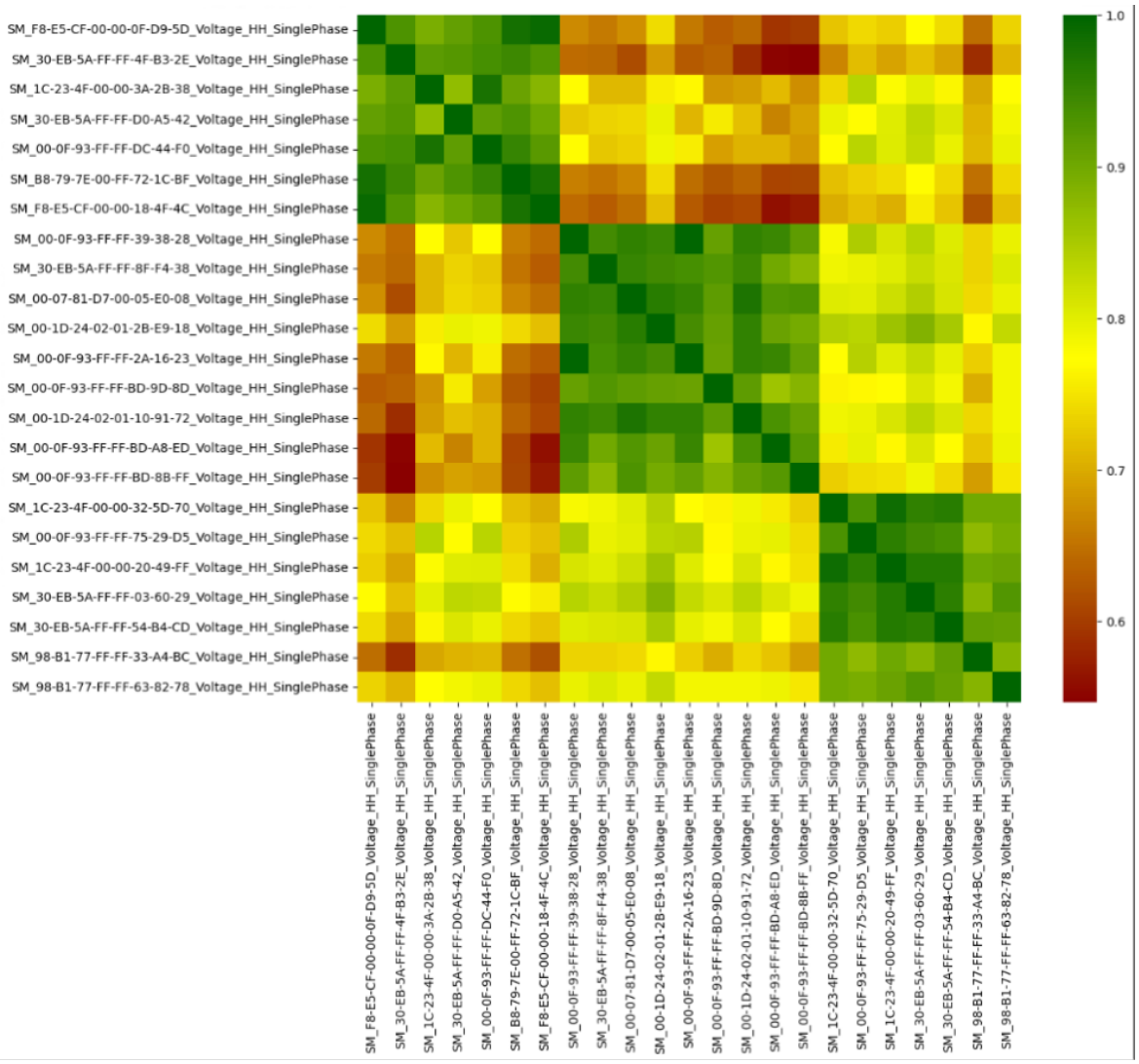


Figure 9: Example smart meter voltage correlation matrix used for hierarchical clustering

Comparison of Method Performance

Comparison of the three methodologies showed that each has a potential role depending on the available data and network configuration. The review found that:

- Approach A, provided the most robust basis for phase identification where suitable monitoring infrastructure was available;
- The clustering techniques could provide useful phase information where monitoring was unavailable;
- Approach C using sequential identification provided a route to wider application where monitored substations were limited;

Additional Network Visibility Findings

The analysis also provided additional insight into network behaviour and phase utilisation. The results showed that significant differences can exist between aggregated feeder-level and localised phase loading. Phase allocation information therefore provided greater visibility of how load is distributed across individual phases and improved understanding of phase unbalance within rural networks.

The analysis also provided a means of reviewing existing connectivity records and identifying locations where recorded information may warrant further investigation, for example where the results show high confidence that customers at a substation have more than one phase, but where the records indicate a single-phase transformer is installed.

Overall

The work demonstrated that HV phase allocation can be inferred from existing smart meter datasets and established a suite of methodologies capable of supporting connectivity assessment under a range of network and data availability conditions. Phase identification accuracies of up to 96.9% were achieved, with more than 91% of single-phase transformers correctly identified.

The project also established repeatable analytical processes, confidence assessment techniques and a practical approach to using smart meter data for connectivity assessment, providing a foundation for the integrated assessment undertaken in WP5 D1 and formed the basis for subsequent evaluation of phase balancing options for a proposed further project in WP5 D2.

Key Deliverables:

- WP3 D1 Selected Algorithms Report v1.0
- WP3 D2 Phase Identification Report (First Release)
- WP3 D3 Phase Identification Report (Smart Meter Data) v1.0
- Smart meter-based phase identification methodologies
- Confidence assessment framework
- Phase assignment datasets for integration within WP5

5.4 Work Package 4: Machine Vision Assessment

The Machine Vision WP4 focused on investigating whether physical network connectivity could be derived from aerial imagery and associated geospatial datasets. Running in parallel with the smart meter analytics undertaken in WP3, the machine vision work provided a complementary approach by assessing connectivity directly from the physical network infrastructure. The aim was to establish whether machine vision techniques could identify conductor arrangements, feeder branches and network structures that could provide evidence of HV connectivity and support phase identification activities. The work demonstrated that, where suitable imagery is available, connectivity information can be extracted from helicopter survey data and converted into a form suitable for engineering analysis.



Figure 10: Reference image

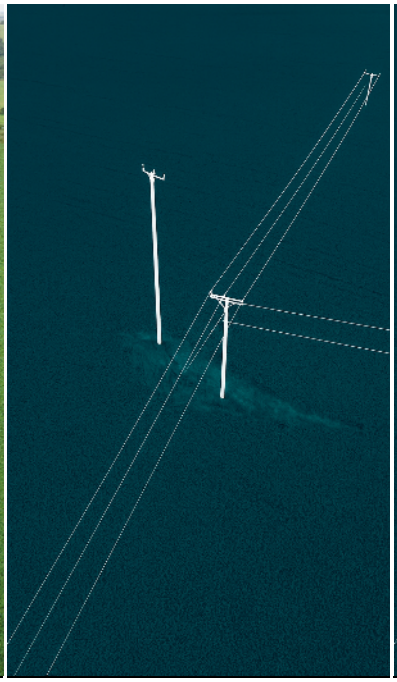


Figure 11: Image with segmentation

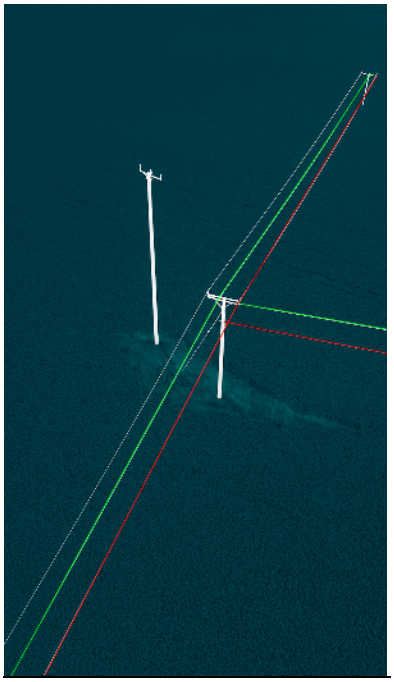


Figure 12: Image with semantic objects

The machine vision assessment was based on existing helicopter survey imagery and associated metadata and LiDAR datasets. Unlike the smart meter approach, which relied on the electrical behaviour of the network, the machine vision work focused on extracting information from the physical network itself.

The first stage of the work involved assessing the suitability of the available imagery for connectivity analysis. This included reviewing image coverage and quality, visibility of conductors, pole structures and junction arrangements, together with the availability of supporting metadata and LiDAR information. This assessment identified significant variation in image quality and highlighted limitations including incomplete capture of single-phase start points, reduced visibility due to helicopter flight altitude, obstructions and gaps in survey coverage.

A significant challenge was that the imagery had primarily been collected for vegetation management and asset inspection purposes rather than connectivity assessment. Consequently, many images did not contain the specific views required to identify conductor connections. More than 10,000 images were reviewed during the work, of which 236 were considered suitable for detailed connectivity assessment, representing a useful image yield of approximately 5%. This demonstrated that image availability and quality were a greater constraint on the approach than the machine vision methodology itself.

Once suitable images had been identified, a series of image processing and machine vision workflows were developed to extract network features. These workflows focused on the identification of:

- Pole locations and structures
- Conductor arrangements and connections
- Pole junction arrangements
- Spur networks
- Distribution substations

The methodology developed beyond individual image classification and feature detection to combine information from multiple images and reconstruct sections of feeder connectivity. Image metadata, including location and orientation information, was used to establish relationships between successive images and link observations to known network assets. LiDAR information provided additional three-dimensional context, supporting identification of pole locations, network geometry and conductor arrangements where imagery alone was inconclusive. The strongest results were achieved when imagery, metadata and LiDAR information were used together.

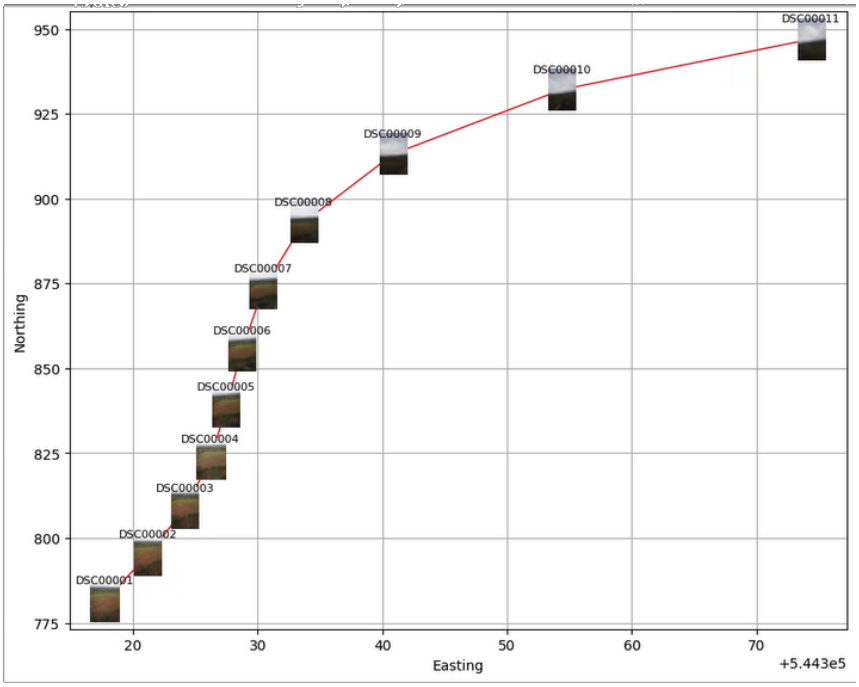


Figure 13: Branch mapping example

The machine vision method was then able to identify specific junction poles at which the feeder connectivity could be determined. Where suitable imagery existed, conductor arrangements could be traced through successive images to establish how different sections of the network were connected.

Table 5-1: Machine vision assessment stages.

Stage	Description
Image Discovery	Identification of relevant images from helicopter survey datasets
Feature Detection	Identification of poles, conductors and network structures
Metadata Processing	Linking images to network locations and assets
LiDAR Integration	Use of spatial information to support interpretation
Topology Reconstruction	Reconstruction of feeder connectivity from multiple data sources
Network Validation	Comparison of observed and recorded network configuration

The methodology was able to identify pole locations, conductor arrangements, line routes, network junctions, spur connections and conductor-pair relationships. Across the four feeders assessed in detail, 95 distinct poles and 52 network connections were identified. Importantly, the machine vision approach was able to identify which two conductors of a three-phase circuit supplied a

single-phase HV spur, including examples of L1-L2, L2-L3 and L1-L3 conductor-pair combinations. This provided an independent assessment of physical network connectivity that could subsequently be compared with the phase assignments produced by the smart meter methodologies.

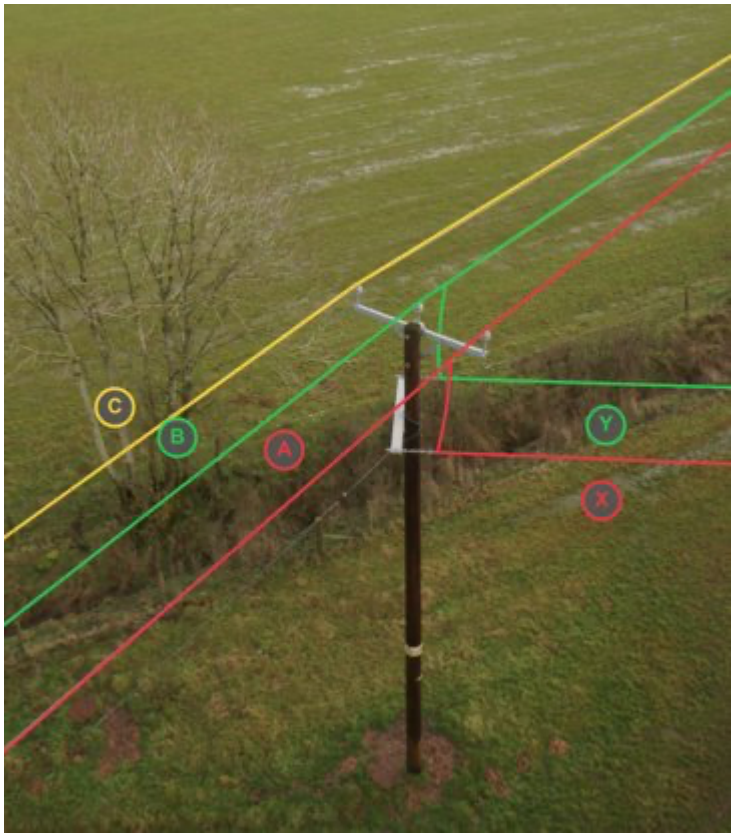


Figure 14: Pole Junction with annotation

As understanding of the datasets improved, increasing emphasis was also placed on reconstructing sections of feeder topology. By combining imagery, metadata, LiDAR datasets and existing network records, the methodology identified relationships between poles, branch connections and downstream network assets. This demonstrated that machine vision could contribute to understanding network connectivity beyond individual asset recognition and could produce structured information suitable for use within broader network connectivity models.

In addition to identifying connectivity, the machine vision workstream investigated how imagery could be used to validate existing network records. Comparison of aerial imagery with recorded network information identified a number of discrepancies, including locations where records indicated three-wire connections while the imagery suggested two-wire arrangements, and vice versa. This demonstrated that machine vision could provide an independent source of evidence to support network record validation and identify locations where further investigation may be beneficial.



Figure 15:Example discrepancy between Electric Office records and observed network configuration at pole 60L9P59.

Overall, WP4 demonstrated that physical network connectivity can be derived from existing aerial imagery and supporting geospatial datasets where suitable coverage is available. The work also highlighted that the principal limitation to wider application is the availability of imagery captured from suitable angles and at sufficient resolution, rather than the ability of the methodology to interpret suitable images. This provides important learning for future helicopter surveys, where survey specification, flight altitude, camera resolution and targeted capture of junctions and spur connections could significantly increase the proportion of imagery suitable for connectivity assessment.

The outputs generated through the machine vision workstream were subsequently taken forward for comparison and integration with the smart meter methodologies in WP5. This provided an independent physical source of connectivity evidence which, when considered alongside the smart meter results, increased confidence in the resulting connectivity assessments.

Table 5-2: Machine vision assessment stages.

Stage	Description
Image Discovery	Identification of relevant images from helicopter survey datasets
Feature Detection	Identification of poles, conductors and network structures
Metadata Processing	Linking images to network locations and assets
LiDAR Integration	Use of spatial information to support interpretation
Topology Reconstruction	Reconstruction of feeder connectivity from multiple data sources
Network Validation	Comparison of observed and recorded network configuration

Source documents:

- WP4 D1 Input Prompt Development (Machine Vision) Report
- WP4 M2 Input Prompt Development (Machine Vision) Report
- WP4 D3 Machine Vision Report (Delivery 4)
- WP1 D2 Visual Data Assessment Report v1.0
- WP5 D1 Project Combined Findings and Learnings Report

5.5 Work Package 5: Comparison and Integration of Outputs

The final technical stage of the project, WP5, focused on bringing together the outputs from the smart meter analytics and machine vision workstreams and assessing how information from multiple sources could be reviewed.

The smart meter workstream provided evidence based on observed electrical behaviour, whilst the machine vision workstream provided evidence derived from physical network configuration. A structured comparison process was therefore developed to enable these different sources of information to be assessed together.

In addition to comparing outputs, this stage focused on establishing a repeatable process for integrating multiple evidence streams into a common analytical framework. This included the development of workflows for:

- Aligning outputs from different methodologies
- Assessing consistency between results
- Reviewing outputs against network records
- Identifying locations requiring further investigation
- Presenting results within a common network model

To integrate the outputs from WP3 and WP4, a common network representation was required. A graph-based network model was developed to link Machine Vision observations at network junctions with downstream transformers and substations.

The graph incorporated:

- Electric Office network topology information
- Pole connectivity
- Feeder structure
- Transformer associations
- Smart meter phase assignments
- Machine Vision conductor observations

This allowed information derived from aerial imagery to be referenced against the same network assets as the phase allocations derived from smart meter analysis and provided a consistent basis for comparison of the two methodologies.

Comparison of Smart Meter and Machine Vision Results

The two approaches assessed connectivity in fundamentally different ways. Smart meter analytics inferred phase relationships from observed voltage behaviour, while Machine Vision identified the physical conductor arrangements and connections visible in aerial imagery. This meant that agreement between the two provided useful independent evidence, while disagreement provided an opportunity to investigate potential limitations, assumptions or data-quality issues.

The first stage compared phase identification results at locations where sufficient data were available from both methodologies.

Table 5-3: Initial Agreement Between Methodologies

Primary Feeder	Matching Substations	Total Compared	Agreement
417560/0041	5	7	71.4%
600017/0034	2	11	18.2%
770003/0001	5	9	55.6%

The initial results showed a number of apparent disagreements, particularly on feeder 600017/0034. Investigation demonstrated, however, that the comparison could not be interpreted simply as a measure of which methodology was correct. Differences could arise from the confidence of individual smart meter classifications, assumptions used to translate physical conductor positions into phase labels, and characteristics of the network itself.

The investigation identified three main factors affecting the comparison:

- **Low-confidence smart meter assignments.** Some discrepancies were associated with smart meters exhibiting relatively weak voltage correlations. In some cases, individual low-confidence results influenced the phase classification assigned to a transformer.
- **Conductor labelling convention.** 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.
- **Potential conductor transpositions.** In some locations, changes in conductor sequence along the feeder provided a potential explanation for differences between the physical conductor position identified by Machine Vision and the electrical phase relationship identified through smart meter analysis.

Revised Comparison Results

Following investigation of the identified discrepancies, agreement between the methodologies improved significantly.

Table 5-4: Agreement Following Investigation

Primary Feeder	Matching Substations	Total Compared	Agreement
417560/0041	6	7	85.7%
600017/0034	11	11	100.0%
770003/0001	8	9	88.9%

The revised results showed a much stronger level of agreement than was apparent from the initial comparison. In many cases, the differences between methodologies were found to be associated with data quality issues, conductor orientation assumptions or unusual network configurations rather than genuine disagreement regarding network connectivity.

Integration of the Two Approaches

Following the comparison, WP5 assessed how the two evidence sources could be used together within the network model.

The work demonstrated that the methodologies provide complementary information. Smart meter analytics provide electrical phase evidence, while Machine Vision provides physical conductor evidence. Bringing these together allows an electrical phase assignment to be associated with the corresponding physical network connection and provides an additional means of validating uncertain results.

The network topology data was central to this process. Machine Vision observations were available only at locations where suitable aerial imagery captured the required conductor connections. By linking these observations to the network topology, conductor-pair information identified at a tee point could be propagated to downstream transformers connected to the same spur.

A degree-of-separation measure was introduced to represent how far a transformer was, in network terms, from a direct Machine Vision observation. This provided an indication of the strength of the propagated evidence, recognising that uncertainty increases as additional network connections are traversed from the directly observed location.

The integrated assessment also demonstrated how the two approaches can complement each other where data coverage is incomplete. Where smart meter data were unavailable or insufficient, Machine Vision observations could provide a phase identification by tracing the identified conductor pair from the tee point to the downstream transformer. Conversely, where suitable aerial imagery was unavailable, the Smart Meter methodology could continue to provide phase identification using voltage data.

The combined evidence also identified applications beyond phase identification. Machine Vision observations identified discrepancies between Electric Office records and the physical network configuration, providing an independent means of identifying locations where existing connectivity records may require validation or correction.

This process would be applied as follows:

1. Machine vision identifies and confirms single- or three-phase transformers and two-wire spurs
2. Voltage data analysis identifies phases of smart meters
3. Phases of confirmed single-phase transformers determined by weighted voting of individual smart meters
4. Phases of transformers on two-wire spurs without smart meter customers assigned based on neighbouring transformers with smart meters
5. Conductor sequence determined at two-wire and single-phase transformer connection by machine vision analysis, using phases derived from smart meter method
6. Where there is confidence that the conductor sequence remains unaltered, phases of transformers or two-wire spur on three-wire sections without smart meters determined using machine vision analysis

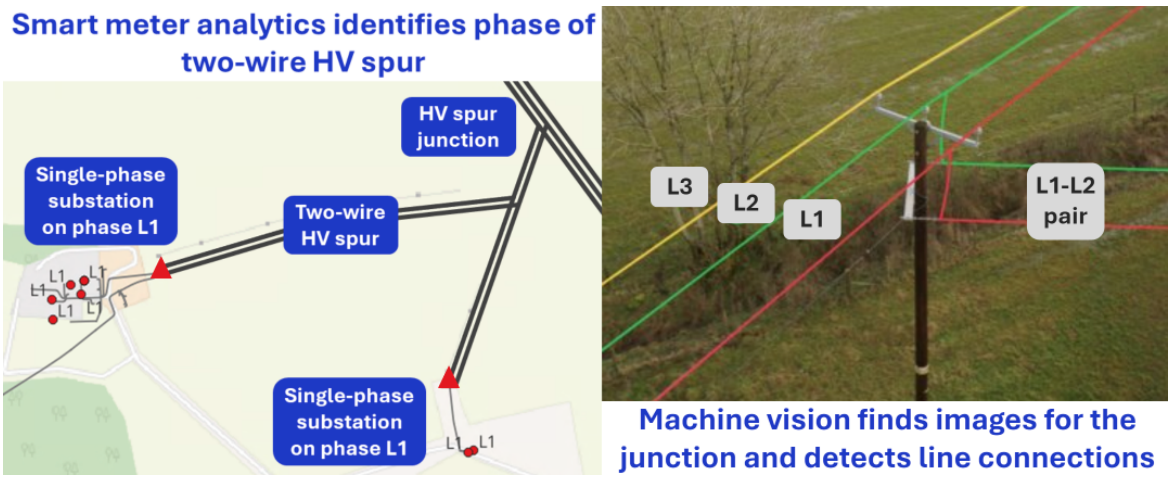


Figure 16:Integrated Phase Identification

Table 5-5: Evidence Sources for Combined Assessment

Evidence Source	Purpose in Combined Assessment
Smart meter analytics	Electrical evidence of phase allocation and connectivity
Machine vision outputs	Physical evidence of conductor connectivity and topology
Network monitoring	Validation and reference data

Asset and connectivity records	Existing network representation used for comparison
GIS and topology data	Spatial context and network relationships
LiDAR datasets	Additional structural information to support physical interpretation

Network Record Validation

One of the recurring themes throughout the project was the relationship between connectivity assessment and network data quality. Whilst the original focus of HV Pilot was to improve visibility of HV phase allocation, the work repeatedly identified differences between recorded network information and information derived from smart meter analysis, aerial imagery and network topology data.

The review of available datasets highlighted limitations in existing connectivity information at an early stage of the project. In particular, the phase connections in transformer asset records were not considered sufficiently complete or reliable to be used as definitive validation data.

The machine vision workstream provided the clearest examples of this. By comparing conductor arrangements visible within helicopter survey imagery against the corresponding Electric Office records, a number of locations were identified where the recorded network configuration differed from the observed physical arrangement.

Examples included:

- locations where network records indicated three-wire to three-wire connections whilst imagery suggested three-wire to two-wire arrangements;
- locations where network records indicated two-wire continuations whilst imagery showed continuation of all three conductors;

These findings showed that machine vision techniques can provide an independent source of evidence for assessing network records and identifying assets that may warrant further investigation.



Figure 17: Discrepancy between the EO network records and the physical network configuration.

The integrated comparison undertaken within WP5 strengthened this finding. Smart meter phase assignments, machine vision observations and existing network records were reviewed together within a common network model. This allowed locations where the different sources of information agreed to be distinguished from locations where inconsistencies existed.

The review found that many apparent discrepancies could be traced to:

- low-confidence smart meter assignments;
- incorrect asset associations;
- conductor orientation assumptions;
- potential phase transpositions; and
- uncertainty within existing network records.

Rather than simply identifying connectivity, the methodologies therefore provided a means of highlighting locations where the underlying data may require further review.

Assessment of Phase Unbalance and Capacity Release Opportunities

Whilst the original focus of HV Pilot was the identification of HV phase allocation and connectivity, the work also provided a better understanding of how load is distributed across individual phases and how this can influence network capacity.

Phase unbalance could be assessed initially by simply considering the number of customers on each phase. However, this could erroneously indicate unbalance where multiple customers have been assigned to one phase to balance a customer with high demand on another phase. A full analysis of unbalance would consider the time-varying demand to take these factors into account.

For the purposes of this project, the unbalance was considered in terms of the annual demands of the customers on each phase, giving an improved estimate of the demand-weighted balance, but without the complication of obtaining detailed smart meter demand data for each customer.

By combining phase assignments generated through the smart meter methodologies with Estimated Annual Consumption (EAC) data and network topology information, the project investigated phase loading across the selected feeders and assessed how phase utilisation varied throughout the network.

Unbalance assessment for the aggregated HV feeder demand

The initial analysis considered phase loading at feeder level by combining identified phase allocations with customer demand estimates derived from EAC data. This provided an indication of how load was distributed across the three phases at the head of each feeder.

The results showed that four of the five feeders assessed appeared relatively balanced when viewed at this level. However, one feeder exhibited a significantly different loading profile, with almost 60% of the assessed demand associated with a single phase.

This showed that significant phase unbalance can exist within rural HV networks and confirmed that the methodologies developed during the project can be used to identify these conditions.

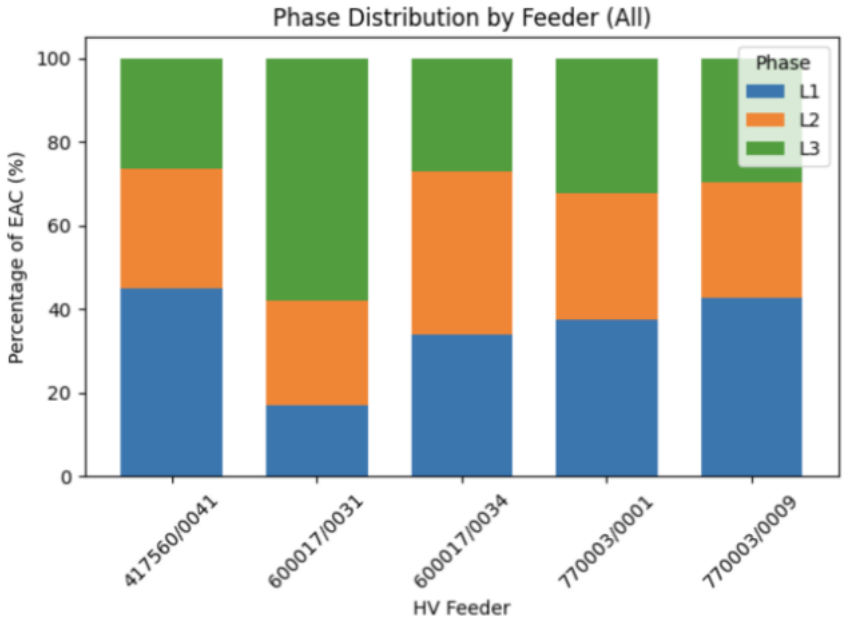


Figure 18: HV feeder phase loading using phase assignments and EAC data.

Unbalance assessment along the HV feeder

The analysis also showed that feeder-level assessments can conceal significant localised unbalance.

Using the identified phase allocations and network topology information, a cumulative loading methodology was developed that aggregated demand from selected feeder endpoints back towards the primary substation. This enabled phase loading to be assessed along the feeder rather than only at the source.

The results showed that phase unbalance often changes significantly along the length of a feeder as additional spurs and substations are incorporated. Whilst loading close to the primary substation may appear relatively balanced, the distribution of demand along the feeder length can be substantially different.

In several cases, the proportion of demand connected to individual phases changed markedly as the analysis moved away from the primary substation and into more remote sections of the network. This showed that localised constraints can exist that are not apparent from feeder-level assessments alone. At the extreme end of a feeder, where a single transformer is connected , all associated demand is naturally concentrated onto the same phase.

Influence of Single-Phase Spur Networks

Across the selected trial networks, the more remote sections of rural feeders were typically characterised by increasing numbers of single-phase transformers connected via single-phase HV spurs. .

These findings highlighted the importance of understanding phase allocation at transformer and along the feeder lines rather than relying solely on aggregated feeder-level averages.

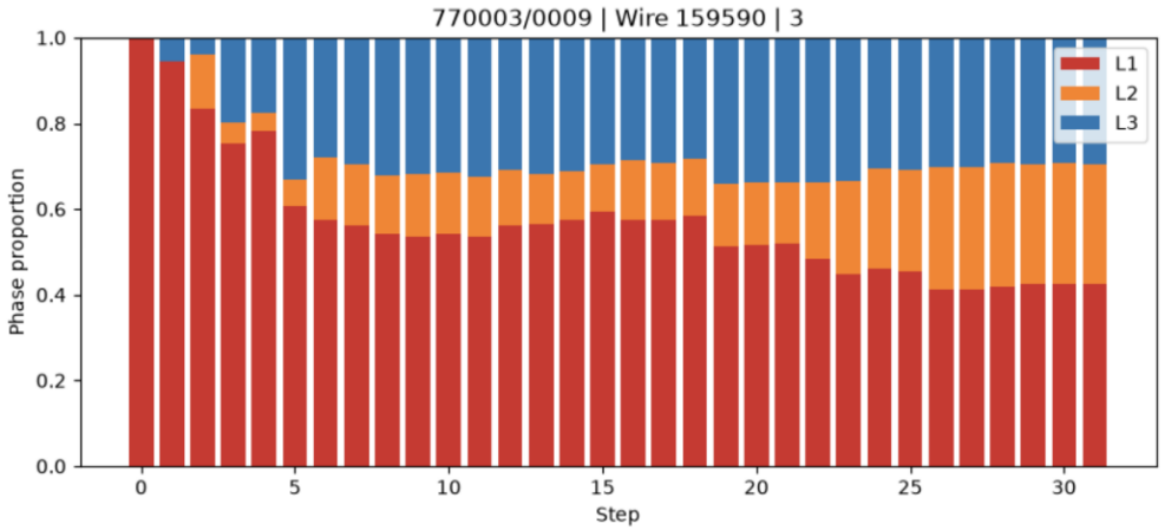


Figure 19: Workflow for calculating cumulative phase loading along an HV feeder.

Capacity Release Opportunities

The work showed that improved visibility of phase allocation creates opportunities to identify and assess potential capacity release interventions.

By understanding which phase supplies individual transformers and spur networks, it becomes possible to investigate:

- opportunities for phase balancing;
- reconfigurationlocation of load between phases;
- targeted validation of connectivity records;
- correction of network data inaccuracies;
- improved utilisation of existing network assets.

Rather than relying solely on reinforcement to address future demand growth, the project showed how improved connectivity information can support lower-cost interventions focused on making better use of existing infrastructure.

The work therefore established a direct link between phase identification and network capacity management. The value of the methodologies developed during the project lies not only in identifying connectivity relationships, but also in helping operators understand how available capacity is distributed throughout the network.

Understanding Hosting Capacity

The original project rationale highlighted the increasing impact of low-carbon technologies such as heat pumps, electric vehicle chargers and distributed generation on rural networks.

The work showed that improved visibility of phase allocation can support more informed assessment of network hosting capacity by providing a clearer understanding of how additional demand or generation would affect individual phases.

By identifying the phase associated with individual transformers and customer groups, the methodologies developed during the project provide a basis for future assessments of:

- low-carbon technology uptake;
- phase utilisation;
- phase balancing requirements;
- local capacity constraints;
- network reinforcement needs.

This provides a more detailed understanding of network behaviour than approaches that assume demand is evenly distributed across all phases.

Overall

The comparison between the Smart Meter and Machine Vision methodologies provided increased confidence in the underlying phase identification results and demonstrated that apparent disagreements can reveal low-confidence smart meter classifications, conductor-orientation uncertainty, potential phase transpositions and network data-quality issues.

Source documents:

- WP5 D1 Project Combined Findings and Learnings Report
- WP3 D3 Phase Identification Report (Smart Meter Data) v1.0
- ENA NIA Project Registration Document – HV Pilot v1.0.

5.6 Project Governance and Dissemination

The project was delivered through a collaborative partnership between National Grid Electricity Distribution (NGED), CGI and Loughborough University. Each partner brought specialist expertise to the project, covering network engineering, data architecture, smart meter analytics, machine vision and academic research.

A formal project governance structure was established at the outset to oversee delivery, manage risks and ensure the work remained aligned with the project objectives. Regular project meetings were held throughout the delivery period, supported by technical workshops, work package reviews and formal meeting minutes. These forums were used to review progress, agree priorities, discuss emerging findings and coordinate activities across the different workstreams.

Given the interdependency between the work packages, regular technical reviews were particularly important. Outputs from WP1 informed the data requirements for WP2, while the analytical methods developed within WP3 and WP4 relied upon the infrastructure and datasets established earlier in the project. Regular review sessions provided opportunities for findings from individual workstreams to be shared, challenged and incorporated into the wider project.

As the project progressed, a number of workshop activities were undertaken to review interim outputs and assess how the methodologies could be applied to real network scenarios. These sessions brought together network engineers, data specialists and project partners to evaluate results, discuss practical implementation considerations and identify areas requiring further investigation.

Knowledge capture formed an important part of the project delivery approach. Learning generated throughout the project was documented through work package reports, technical deliverables, project meeting minutes and periodic progress updates. This ensured that methodological developments, assumptions, challenges and decisions were recorded as the project evolved.

The project also placed emphasis on wider dissemination of learning beyond the immediate project team. Findings were shared through internal innovation channels and discussions with network planning and engineering stakeholders. This helped ensure that emerging learning could be considered within wider business activities and future innovation opportunities.

In addition to internal dissemination, outputs from the project were used to support external knowledge sharing activities. Project findings were presented through industry engagement activities and formed the basis of a CIRED conference paper focused on the identification of phase allocation and phase unbalance on rural HV networks. The paper provided an opportunity to share learning with a wider audience and gather feedback from industry peers working on similar challenges.

The Living Innovation material developed during the project was also used to communicate the objectives, methodologies and emerging opportunities associated with improved visibility of HV phase allocation. This provided a concise illustration of how smart meter analytics and machine vision could be used together to improve understanding of network connectivity and support future network planning activities.

Throughout the project, governance and knowledge-sharing activities ensured that technical developments remained aligned with project objectives, that findings could be reviewed by a broad range of stakeholders and that learning generated through HV Pilot could be captured and shared both within NGED and across the wider electricity industry.

Table 5-6: Summary of project dissemination activities.

Activity Type	Purpose
Project Steering Groups	Governance and oversight
Technical Workshops	Review of methodologies and findings
Work Package Reviews	Validation of interim outputs
Internal Stakeholder Engagement	Knowledge transfer within NGED
Living Innovation Material	Communication of project concepts and opportunities
CIRED Conference Paper	External dissemination of project learning

6. Performance Compared to Original Aims, Objectives and Success Criteria

The project objectives and success criteria were assessed using the outputs generated throughout the project and the evidence gathered during delivery of each work package.

The following tables summarise performance against the original project objectives and success criteria.

Table 6-1: Performance compared to project objectives

Objective	Status	Performance
Explore solutions for determining HV phasing	Complete	Multiple approaches were developed and assessed using smart meter data, network monitoring information, aerial imagery and LiDAR datasets. These approaches provided alternative methods for assessing phase allocation across rural HV overhead line networks.
Integrate and manage data from multiple sources	Complete	A dedicated data environment was established to integrate smart meter data, monitoring information, network records, aerial imagery and LiDAR datasets within a common analytical framework.
Develop algorithms using smart meter data to identify HV phase allocation	Complete	Several smart meter-based methodologies were developed, tested and refined using data from the selected trial feeders. The work included the development of correlation-based, clustering and confidence assessment techniques.
Identify a methodology to address HV connectivity gaps	Complete	Complementary smart meter and machine vision methodologies were developed and evaluated, providing alternative means of assessing network connectivity where phase information was incomplete or unavailable.
Leverage new technologies, including smart meters, monitoring systems and aerial imagery	Complete	The project incorporated smart meter data, network monitoring, aerial imagery, machine vision techniques, LiDAR datasets and cloud-based analytical tools within a single programme of work.
Apply the developed algorithms to real-world network scenarios	Complete	The methodologies were applied using operational network data from selected rural HV feeders and assessed across a range of network configurations and data availability scenarios.
Assess performance and identify factors influencing results	Complete	The influence of data quality, smart meter penetration, monitoring availability, image quality, network configuration and validation opportunities was assessed throughout the project.
Capture learning and disseminate findings	Complete	Learning was captured through technical reports, work package deliverables, project reviews, technical workshops, dissemination activities and conference paper development.

Table 6-2: Status of project success criteria

Success Criteria	Achieved	Performance
Successfully assessed and evaluated network data to identify the project sample areas	✓	Network records, monitoring data, smart meter availability, aerial imagery and LiDAR datasets were assessed to identify suitable trial networks and supporting datasets.
Analysed helicopter images to determine their usability and relevance for applying machine vision techniques	✓	A structured review of available imagery, image metadata and LiDAR datasets was undertaken to assess suitability for connectivity analysis and machine vision development.
Compiled comprehensive reports on network data assessments, visual data analysis and the outcomes of area selection	✓	Network assessment, imagery assessment and feeder selection activities were documented through dedicated project deliverables.
Identified and integrated suitable hardware, software and interfaces to facilitate efficient data collection, processing and analysis	✓	A dedicated datastore, Azure-based analytical environment and supporting data integration processes were developed to support project activities.
Thoroughly tested and evaluated algorithms to ensure they met the specified use case requirements	✓	Smart meter and machine vision methodologies were developed and assessed using representative network datasets and selected trial feeders.
Produced detailed reports on selected algorithms, method development and learning outcomes from applying these algorithms	✓	Technical reports were produced describing methodology selection, analytical development, validation activities and project learning.
Developed a machine vision capability for phase identification, supported by methodology development, testing and performance assessment	✓	Machine vision workflows were developed using aerial imagery, image metadata and LiDAR information to assess physical network connectivity.
Clearly summarised project findings, developed the business case and delivered supporting project outputs	✓	Findings from all work packages were consolidated through the combined findings report, technical deliverables and dissemination activities.

6.1 Overall Assessment

All planned work packages were completed and the project met the objectives and success criteria established at the outset.

The project delivered methodologies for assessing HV phase allocation using both smart meter analytics and machine vision techniques. A supporting data environment was also established to integrate multiple datasets and provide a common framework for analysis.

The work completed during the project provided sufficient evidence to assess the applicability of the proposed approaches, understand the factors influencing their performance and evaluate their suitability for addressing gaps in existing HV connectivity information.

7. Required Modifications to the Planned Approach during the Course of the Project

The overall objectives and scope of the project remained unchanged throughout delivery. However, several refinements were made to the planned approach as understanding of the available datasets improved.

The most significant modification related to the machine vision workstream. Early assessments of the available helicopter survey imagery identified that much of the imagery had been collected for vegetation management and asset inspection purposes rather than connectivity analysis. As a result, many images did not contain the conductor junctions, branch connections and viewing angles required to support detailed connectivity assessment. This led to a refinement of the feeder selection process and a greater emphasis on identifying feeders where suitable imagery and supporting datasets were available.

The machine vision methodology also evolved during the project. Initial work focused on determining whether conductor connectivity could be identified directly from imagery. As understanding of the datasets improved, greater use was made of image metadata, LiDAR information and existing network records to support topology reconstruction and interpretation of network structures.

Within the smart meter workstream, the planned approach was expanded to include multiple analytical methodologies rather than relying on a single technique. This was driven by the variation in data availability across the selected feeders and the need to assess alternative approaches where monitored reference substations were unavailable. Additional confidence assessment and validation processes were also introduced to provide a more robust basis for evaluating the outputs.

The project also placed greater emphasis on data integration than originally anticipated. Early activities identified that information required for connectivity assessment was distributed across multiple systems and formats. As a result, additional effort was directed towards the development of a dedicated datastore, network graph models and supporting data integration processes to ensure that information from different sources could be analysed consistently.

These modifications did not alter the overall objectives of the project but ensured that the methodologies remained aligned with the characteristics and limitations of the available datasets, allowing the project to maximise the value obtained from both the smart meter and machine vision approaches.

8. Project Costs

Final project costs can be viewed in the table below.

Table 8-1: Overall Project Spend

Activity	Budget	Actual	Variance (%)
Contractors	£664,144	£664,144	0.0
NGED Internal Costs	£25,490	£25,490	0.0
Dissemination	£5,000	£0	-100.0
Contingency	£69,463	£0	-100.0
Totals	**£764,097**	**£689,634**	**-9.7**

9. Lessons Learnt for Future Projects and outcomes

The project generated learning in a number of areas including data integration, smart meter analytics, machine vision, validation techniques and the practical application of connectivity information. The lessons captured in Table 9-1 are intended to support future innovation projects, inform potential deployment activities and provide transferable learning that may be relevant to other network operators undertaking similar work.

Table 9-1: Lessons Learnt and Future Application

Topic	Learning	Future Application / Recommendation
Data Selection, Quality and Integration	The availability, quality and structure of the available data had a greater influence on project delivery than originally anticipated. Significant effort was required to locate, cleanse, reconcile and integrate smart meter data, monitoring information, network records, imagery and LiDAR datasets before meaningful analysis could begin. Establishing a common analytical environment and consistent network representation proved essential in supporting subsequent analytical activities. As noted on previous projects, there is an ongoing concern that some smart meters do not return time-series voltage data, or cannot be reconfigured to change the reporting time interval. This limits the usability of these meters for analysis, and also limits visibility of voltage variations at the customer connection. There is a further concern that the start times for voltage measurement periods differ between smart meters. However, no problems were encountered with smart meter clock time synchronisation.	Future projects should undertake detailed data assessments during project initiation and treat data engineering, integration and governance as core project activities rather than supporting tasks. Common data environments should be established early to enable efficient comparison of outputs generated from multiple sources.
Smart Meter Analytics	Existing smart meter voltage data provided a useful source of information for assessing HV phase allocation. Phase identification using the smart meter method works well, giving valid phase indications for around 90% of substations. Voltage variations on each phase are sufficiently consistent to enable phase identification, by correlation of smart meter voltages between distant substations on an HV feeder The method performs better where substation LV monitoring is available (Approach A), but good results can be achieved without the need for substation this additional data (Approach C). Where there is no substation monitoring, the method starts by identifying phases of customers at a three-phase reference substation, One or	Future development should focus on extending validation across a larger population of feeders, improving automation and embedding confidence assessment within any operational implementation. Deployment should support multiple complementary analytical approaches rather than relying on a single methodology.

Topic	Learning	Future Application / Recommendation
	more of these customers on each phase can act as a proxy for the monitoring data. Customers at other substations are then assigned a phase by finding the best correlation with customers from the reference substation. If there is no substation monitoring, identified phases are group clusters rather than actual phases L1, L2, L3 Errors in phase identification appear to be due, at least partly, to voltage drops on LV feeders that are specific to local groups of customers Phase identification accuracy is therefore limited more by the LV feeder voltage drops than by the separation distance of substations along the HV feeder The smart meter method works independently of machine vision data but can be enhanced where image data is used to confirm that HV spurs or transformers are single-phase. A single phase can then be resolved if results from multiple customers are ambiguous, for example by selecting a weighted majority. A key requirement for the smart meter method is that HV feeders should include at least one three-phase substation, and this is the case for all but 20 HV feeders in the set assessed. Ideally, only one smart meter is needed at the single-phase substations but several smart meters improves the likelihood that a customer will be located closer to the substation, avoiding the impact of LV voltage drops, and allows for occasional interruptions in the voltage data.	
Machine Vision and Supporting Data	Machine vision techniques were capable of identifying physical network connectivity where suitable imagery existed. Conductor connections can be detected, even when human interpretation is less certain The suitability of the available imagery proved to be one of the main factors influencing performance. Images for many feeders were found to be unusable, and many junctions were not covered by the helicopter survey There were few examples in the available images of single-phase transformer connection onto three-wire feeders, and there are fewer images of two-wire junctions than of three-wire junctions Given the gaps in the aerial survey and the presence of underground cable sections, it is not possible to trace end-to-end conductor	Future image capture programmes should consider connectivity assessment requirements during survey specification. Machine vision development should continue to combine imagery, metadata, LiDAR information and network records rather than relying on image analysis alone.

Topic	Learning	Future Application / Recommendation
	connectivity, so phase identification relies on conventions to determine the left-to-right conductor sequence on overhead lines These conventions appear to be respected for most overhead lines, but uncertainty limits the confidence of phase identification, even though conductor topology can be determined. Where the conductor orientation convention is untrusted, phases can be identified using the smart meter method, so that a local conductor orientation can be derived using the machine vision results. On sections of line where the conductor orientation remains the same, or where it can be derived from the machine vision results, phase identifications from the smart meter method can be extended to find phases at nearby substations with no smart meter customers. Conductor topology at junction poles can be determined for three-wire connections, in addition to the two-wire HV spurs originally intended for the analysis	
Validation Using Multiple Evidence Sources	Confidence in the outputs increased significantly when independent evidence sources reached the same conclusion. Smart meter analytics, machine vision outputs, monitoring data and network records each provided different perspectives on network connectivity and were most valuable when considered together.	Future solutions should adopt a multi-source approach and avoid relying on a single dataset or methodology. Validation should remain a fundamental part of any future deployment activity.
Network Records and Network Visibility	Comparing analytical outputs against recorded network information highlighted opportunities to identify missing, incomplete or inconsistent connectivity records.	Connectivity assessment techniques should be considered as a means of supporting network record validation and improving the quality of network information used by planners, engineers and operational teams.
Future Deployment	The practicality of deployment is influenced not only by analytical performance but also by data availability, automation, confidence assessment and integration with existing business processes. Smart meter analytics currently appears to offer the clearest route towards wider application, while machine vision provides valuable complementary evidence and validation.	Future work should focus on operationalisation, automation and integration of smart meter methodologies into existing planning and network analysis processes, while continuing to develop machine vision as a complementary capability.
Applications Beyond Phase Identification	One of the most significant lessons from the project was that the value of improved connectivity information extends beyond identifying phase allocation. Improved visibility of network connectivity can be used to support	Future activities should focus on using improved network visibility to support planning, modelling, phase balancing, connection assessments and broader

Topic	Learning	Future Application / Recommendation
	network modelling, understanding of phase unbalance, assessment of capacity constraints and validation of existing records.	network optimisation activities rather than treating phase identification as an objective in isolation.

Overall, the project demonstrated that successful connectivity assessment depends on a combination of data quality, analytical methodologies and independent validation. The wider value of the approach lies in using improved visibility of network connectivity and phase relationships to support network model.

10. The Outcomes of the Project

10.1 Summary

- The smart meter method of phase identification has been demonstrated and provides results with high confidence for over 90% of single-phase substations.
- Clearly, the method can only be applied for substations where one or more customers has a smart meter. Phase identification results were considered valid with higher confidence if multiple customers at the single-phase substation were identified with the same phase.
- This confidence is increased where results from the machine vision method can confirm that a transformer is single-phase, as in some cases the transformer records are uncertain.
- Although the project trial sample only included detailed analysis of seven HV feeders, these feeders were unusually long and included many rural substations. This gives good confidence that the method will work well on shorter and less challenging HV feeders. However, further evidence is needed that the method will perform well more generally. There are also some manually set threshold parameters that may need to be adjusted to give good results for other HV feeders.
- The phase identification method provided lower correlation results for substations on the customer side of a voltage regulator, when the selected reference substation was on the primary side. Similar issues may arise with other transformer assets that are installed along HV feeders, and the methods were not developed here to allow for these.
- Although a greater number of feeders would need to be analysed to demonstrate that phase identification performs well across all license areas, there is no indication from the trial feeder results that the method would not be applicable more widely.
- The smart meter phase identification method gives results with higher confidence when LV substation monitoring data is available to act as a voltage reference. This monitoring data also allows phase clusters to be resolved into named phases L1 L2 L3. This highlights the benefit of continuing to install substation monitoring.
- Where there are no substations on the HV feeder with monitoring installed, single-phase substations are clustered into groups but there may be no reference available to resolve these clusters into phases L1 L2 L3. This is not a concern from the perspective of power-flow modelling, phase information would be needed to implement conductor changes on the line. If necessary, this can be obtained from phase testing instruments.
- As with the SMITN NIA project, the smart meter phase identification was constrained by the lack of time-series voltage data from some smart meters, by problems in reconfiguring them to 10-minute resolution, and by the lack of a common timeframe for reporting averaged data. Further investigation of these issues with the DCC would enable greater use to be made of the existing smart meter infrastructure in future.
- The machine vision method also performed well and could be adopted to identify the conductor connections at two-wire junctions.
- On many feeders there were insufficient images with good quality and only around 20% of those selected for review were considered suitable for processing. With current image availability, this would limit the potential for this method to be applied, though we expect it

would be possible for the spatial granularity and camera resolution of the image capture to be improved.

- If the conductor phase orientation is known to follow a defined convention (e.g. L1 on the right looking away from the primary), then the machine vision can identify phases in addition to the conductor connectivity.
- Higher resolution images would improve results from the machine vision method. This could include more frequent captures for better spatial resolution along the flight path, giving multiple captures for each transformer or junction, or images captured using drones flying nearer to the connections and with observations from multiple angles.
- Alternatively, if the phase of a single-phase transformer or two-wire spur is known from the smart meter method, then the machine vision method can be used to derive the local conductor phase orientation. This might also allow the phases of nearby substations with no smart meter customers to be determined.
- Where data is available to support both the smart meter method and the machine vision method, and where there is confidence that the conductor phase orientation follows a defined convention, then phase identifications can be compared to give higher confidence in the results.
- Email information from HV planners has been used in HV Pilot to avoid applying data analysis when data would be inconsistent due to network topologies, or when open points are moved for maintenance work. Avoiding this manual process, the analysis could compare the network configuration from PowerOn with the normal state from Electric Office to ensure aerial survey and smart meter data are consistent.
- Further work is needed to automate processing of aerial survey data, and to provide increased confidence that the phase identification methods can be applied over a wider range of feeders. However, the core methods have been demonstrated to perform well on the trial feeders, such that a future innovation project can move on to consider how the phase information derived here could be used. This would identify specific locations where phase connections could be reconfigured to release capacity and investigate how a phase-aware planning process could enable new connections to be accepted faster.

10.2 Technology Readiness and Deployment Potential

HV Pilot was registered with a Technology Readiness Level (TRL) of 4 at project commencement and a target TRL of 7 at project completion.

The project showed that smart meter analytics, machine vision techniques and integrated connectivity assessment methodologies can be applied using operational datasets from representative rural HV networks. The methodologies were developed, tested and demonstrated using real smart meter measurements, monitoring data, network records, aerial imagery and LiDAR datasets rather than purpose-built research datasets.

The project identified a number of areas that would benefit from further development before deployment at scale, including:

- validation across a larger and more diverse feeder population;
- increased automation of analytical workflows;
- management of areas with limited smart meter penetration;
- improved image quality, for example by using drone surveys;
- integration with existing planning, modelling and asset management systems; and
- processes for maintaining connectivity information as network configurations evolve.

The work also showed that the methodologies are at different stages of deployment readiness. Smart meter-based approaches currently provide the clearest route towards wider application due to the availability of the required data and the consistency of the results obtained during the project. The machine vision methodology provided useful physical evidence of network connectivity and supported validation of network records, although its wider application is currently more dependent on the availability of suitable imagery.

The project has significantly increased the maturity of the methodologies beyond their original proof-of-concept stage. However, the work was undertaken on a relatively small number of feeders selected on the basis of data availability and suitability. Further validation across a broader range of network configurations and geographical areas would therefore be required before the methodologies could be considered ready for widespread operational deployment.

The outcomes of the project are considered consistent with progression from **TRL4 to TRL7**. The methodologies have been demonstrated in a relevant operational environment using real network datasets and representative rural HV feeders. Further large-scale validation, automation and business integration activities would be required before BAU rollout.

10.3 Opportunities for Future Development

The work completed through HV Pilot identified a number of areas where further development could build on the learning generated during the project and increase its practical application within network planning and operation.

Smart Meter Analytics

The smart meter methodologies delivered encouraging results across the selected trial networks and showed that existing voltage measurements can be used to identify HV phase allocation and connectivity relationships. The work was undertaken on a relatively small number of feeders and further validation would be beneficial to understand how the methodologies perform across a wider range of network configurations.

Future work could focus on:

- validating the methodologies across a larger and more diverse feeder population;
- assessing performance in urban and mixed network environments;
- further refining confidence assessment techniques;
- increasing automation of data preparation and analytical workflows;
- integrating outputs into network modelling, planning and connections processes.

The project also showed that smart meter data can support activities beyond phase identification, creating opportunities to use phase allocation information within wider assessments of network loading, flexibility and low-carbon technology connections.

Machine Vision

The machine vision work showed that physical connectivity information can be extracted from aerial imagery where suitable image coverage exists. The principal limitation identified during the project was not the analytical methodology itself, but the availability of imagery containing suitable views of conductor junctions, pole structures and spur arrangements.

Future work could investigate:

- higher-resolution helicopter survey imagery;
- drone-based image collection targeted at connectivity assessment;
- image capture specifications designed specifically for network reconstruction activities;
- enhanced conductor tracking and topology reconstruction techniques;
- greater automation of image interpretation and confidence assessment;
- integration of imagery with additional datasets such as thermal imaging or enhanced LiDAR surveys.

Further work could also assess whether connectivity assessment requirements can be incorporated into existing inspection and vegetation management survey programmes.

Integrated Connectivity Assessment

One of the strongest findings from the project was the value of combining multiple independent evidence sources. Smart meter analytics, machine vision outputs and network topology information each provided different perspectives on network connectivity and collectively produced greater confidence than any individual methodology used in isolation.

Potential areas for further development include:

- extending the integrated approach to a larger population of feeders;
- developing automated confidence scoring methodologies that utilise multiple evidence sources;
- periodic reassessment of connectivity information as networks evolve;
- integration of connectivity assessment outputs with operational systems;
- automated identification of locations requiring investigation or validation.

The graph-based network modelling techniques developed during the project also provide a basis for wider network visibility applications and could support future work relating to topology verification, connectivity assessment and data quality improvement.

Network Record Improvement

The project showed that both smart meter analytics and machine vision techniques can assist with validation of existing network records. Several examples were identified where observed network connectivity differed from recorded information, highlighting opportunities to improve the quality of asset and connectivity data.

Future work could investigate:

- systematic validation of network records using analytical outputs;
- risk-based identification of assets requiring further verification;
- automated flagging of potential discrepancies between records and observations;
- integration of connectivity assessment techniques into asset data management processes;
- development of workflows to support ongoing maintenance of connectivity information.

Improved network records have the potential to support more accurate network modelling, planning and operational decision-making.

Phase Balancing and Capacity Release

The work carried out during WP5 showed that improving visibility of phase allocation provides significantly greater insight into network loading and phase utilisation. One of the most promising areas for further investigation is the use of this information to identify opportunities for phase balancing and capacity release.

Potential future activities include:

- quantifying the level of capacity release achievable through phase balancing;
- identifying locations where localised phase unbalance constrains network capacity;
- assessing phase balancing interventions as alternatives to reinforcement;
- developing tools to support phase utilisation assessments;
- investigating how phase information could be used in the new connections process.

Operational Deployment and Scale-Up

HV Pilot demonstrated technical viability on a limited number of representative feeders. A logical next step would be to assess performance across a larger and more varied network population to understand scalability, repeatability and operational applicability.

Before wider deployment could be considered, future work would benefit from:

- validation across larger network populations;
- increased automation of analytical workflows;
- assessment of operational costs and benefits;
- integration with existing business processes;

- development of governance arrangements for maintaining connectivity information over time;
- evaluation of deployment strategies and implementation pathways.

This would provide the evidence required to determine how the methodologies developed during HV Pilot could be incorporated into routine business activities.

Wider Innovation Opportunities

Although the project originated as a solution to improve visibility of HV phase allocation, the learning generated identified a broader set of opportunities relating to network visibility, data quality and asset utilisation.

Areas for future innovation include:

- network digital twins incorporating phase allocation information;
- automated network record validation systems;
- capacity assessment tools informed by actual phase utilisation;
- advanced phase balancing methodologies;
- improved hosting capacity assessment for low-carbon technologies; and
- wider applications of machine vision and smart meter analytics within network operation.

The project therefore established not only a set of connectivity assessment methodologies, but also a foundation for future innovation activities focused on improving network visibility, data quality and utilisation of existing network assets.

11. Data Access Details

Detail the data there is or will be available by the end of the project to share using the data sharing policy. *(Link to project data page on innovation website (/www.nationalgrid.co.uk/innovation/contact-us-and-more)*

12. Foreground IPR

The project generated foreground intellectual property relating to:

- Smart meter-based phase identification methodologies for HV transformers and feeder branches.
- Machine vision methodologies for identifying network connectivity from aerial imagery and LiDAR datasets.
- Enhancements to existing phase identification and machine vision techniques.
- Data integration, validation and confidence assessment processes.
- Graph-based network modelling methods used to combine multiple sources of connectivity evidence.
- Project reports, findings and supporting technical documentation.

Foreground IPR generated during the project is owned by the originating project partners in accordance with the project collaboration agreements and NIA governance arrangements.

The methodologies and learning generated through HV Pilot may be of interest to other network operators seeking to improve understanding of HV phase allocation, network connectivity, phase unbalance and network record quality.

If access to specific methodologies or further information relating to project IPR is required, interested parties should contact National Grid Electricity Distribution using the contact details provided in Section 14.

13. Planned Implementation

The methodologies developed within HV Pilot are not currently planned for immediate business-as-usual implementation across the NGED network. The project demonstrated the technical viability of smart meter analytics, machine vision techniques and integrated connectivity assessment using representative rural HV feeders. Further validation across a larger and more diverse feeder population would be required before wider deployment could be considered.

Of the approaches assessed, smart meter analytics currently provides the clearest route towards future implementation due to the availability of the required data and the performance achieved during the project. Machine vision techniques also demonstrated value, particularly in supporting network record validation and providing independent physical evidence of network connectivity, although wider application would benefit from improved image availability and image capture arrangements.

Future work should focus on:

- Validation across a larger population of feeders.
- Increased automation of analytical workflows.
- Integration with planning, modelling and asset management processes.
- Assessment of phase balancing and capacity release opportunities.
- Further development of image capture approaches to support machine vision applications.

No plans currently exist to submit a notice under Special Condition 6E (The Innovation Roll-out Mechanism) or Charge Restriction Condition 3D (The Innovation Roll-out Mechanism). The outcomes of HV Pilot provide a foundation for further development and validation activities before any decision regarding wider deployment is made.

14. Contact

Further details on this project can be made available from the following points of contact:

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15. Glossary

Abbreviation	Term
AI	Artificial Intelligence
API	Application Programming Interface
BAU	Business As Usual
CGI	CGI UK Ltd
CIRED	International Conference and Exhibition on Electricity Distribution
CSV	Comma-Separated Values
CROWN	NGED Customer and Network Data System
DCC	Data Communications Company
DER	Distributed Energy Resource
DNO	Distribution Network Operator
EAC	Estimated Annual Consumption
EHV	Extra High Voltage
EO	Electric Office
ERD	Entity Relationship Diagram
ETL	Extract, Transform and Load
EV	Electric Vehicle
GIS	Geographic Information System
GPS	Global Positioning System
GridKey	Lucy Electric LV Monitoring System
HV	High Voltage
INM	Integrated Network Model
JSON	JavaScript Object Notation
L1	Phase 1
L2	Phase 2
L3	Phase 3
LCT	Low Carbon Technology
LiDAR	Light Detection and Ranging
LV	Low Voltage
MPAN	Meter Point Administration Number
MV	Machine Vision
NGED	National Grid Electricity Distribution
NIA	Network Innovation Allowance
ODS	Operational Data Store
PDR	Phase Detection Rate
PRESense	Presense Technologies LV Monitoring System
PV	Photovoltaic
QGIS	Quantum Geographic Information System
Rand Index	Statistical measure used to compare clustering results

Abbreviation	Term
Roames	Fugro aerial imagery and network visualisation platform
SCADA	Supervisory Control and Data Acquisition
SCD Type 2	Slowly Changing Dimension Type 2
SIF	Strategic Innovation Fund
SM	Smart Meter
SMETS	Smart Metering Equipment Technical Specifications
SMITN	Smart Meter Innovation and Testing Network
SQL	Structured Query Language
TRL	Technology Readiness Level
VIPQ	Voltage, Current, Active Power and Reactive Power
VisNet	EA Technology LV Monitoring System
WP	Work Package

16. Appendices

Project Deliverables and Supporting Documentation

All publicly available project deliverables can be accessed via the HV Pilot project webpage here https://commercial.nationalgrid.co.uk/innovation/projects/hv-pilot-high-voltage-phase-identification

Project Direction and Registration

- Project Registration Document

Work Package 1 – Network Data Assessment and Trial Area Selection

- WP1 D1 – Network Data Assessment Report
- WP1 D2 – Visual Data Assessment Report
- WP1 D3 – Area Selection Report

Work Package 2 – Data Architecture and Analytical Environment

The following report is not publicly available as it contains proprietary intellectual property.

- WP2 D1 – Data Architecture and Data Store Overview – Not published

Work Package 3 – Smart Meter-Based Phase Identification

- WP3 D1 – Selected Algorithms Report
- WP3 D2 – Phase Identification Report (First Release)
- WP3 D3 – Phase Identification Report (Smart Meter Data)

Work Package 4 – Machine Vision Connectivity Assessment

- WP4 D1 – Input Prompt Development (Machine Vision) Report
- WP4 D3 – Machine Vision Report

Work Package 5 – Integrated Connectivity Assessment and Future Development

- WP5 D1 – Project Combined Findings and Learnings Repot
- WP5 D2 – HV Pilot Follow-On Project Report