Notes on Completion: Please refer to the appropriate NIA Governance Document to assist in the completion of this form. The full completed submission should not exceed 6 pages in total.

NIA Project Registration and PEA Document

Date of Submission

Oct 2026

Project Reference Number

NIA3_NESO011

Project Registration

Project Title

Volta – Locational Real Time Prediction (LRTP)

Project Reference Number

NIA3_NESO011

Project Licensee(s)

National Energy System Operator

Project Start

January 2027

Project Duration

1 year and 1 month

Nominated Project Contact(s)

Innovation@neso.energy

Project Budget

£640,000.00

Summary

The project will apply state-of-the-art forecasting at high spatial and temporal granularity to support scheduling and decision-making within control room balancing teams. It will assess the current data landscape, develop and test scalable forecasting approaches across hundreds of existing, modified and new network nodes, and explore model explainability, including the use of AI agents. The project has three phases:

1) assess data availability, quality and user requirements (4 months);

2) build a proof-of-concept model and test scalability across hundreds of network nodes (5 months); and

3) evaluate model explainability options, including AI agents (3 months). Key risks include the availability and quality of metered data at GSP (Grid Supply Point) level, ongoing network reconfiguration, and availability of computational resources during testing.

Preceding Projects

NIA2_NESO105 - Volta: Real Time Prediction

Third Party Collaborators

University of Oxford

Nominated Contact Email Address(es)

Innovation@neso.energy

Problem Being Solved

The Control Room currently relies on a relatively blunt tool approach (i.e a limited, high-level approach to estimating locational demand within operational scheduling timeframes, which may not provide the level of precision required for more targeted operational decisions) to estimating locational demand within operational scheduling timeframes. These estimates are used to assess group constraint violations and inform balancing actions. Where locational demand forecasts are inaccurate or insufficiently granular, this can lead to inefficient use of the transmission network, sub-optimal reserve allocation, and increased balancing costs. At present:

1. Current GSP forecasts are produced discretely, typically twice daily, and allocate national demand to constraint groups using proportional weighting.

2. This approach creates uncertainty and variability in forecasts, which can require larger operational margins.

3. There is currently no model that provides high-resolution, locationally specific demand insight for control room decision-making.

4. Redispatch between network zones is a significant contributor to NESO balancing costs, estimated at £1.7bn.

5. Increasing spatial variation and volatility in generation and demand are expected to place further strain on the system.

Undertaking this project will build on the successfully delivered NIA Volta: Real Time Prediction (NIA2_NESO105) project and seeks to extend its capability for practical business use.

The Volta: Locational Real Time Prediction (LRTP) project is expected to design, model, and evaluate a scalable forecasting architecture that supports an adaptive locational demand model. Subject to data availability, the model will provide spatially resolved, probabilistic predictions at high temporal granularity, including sub-10-minute forecasts of electricity demand, generation, and line flows. The intended purpose is to improve control room visibility, support better operational decisions, and enable more efficient balancing mechanism reserve allocation and dispatch resulting in:

1. A scalable adaptive forecasting model that can provide input to Volta and support future operational integration.

2. Improved visibility of near-term network constraints, enabling earlier and better-informed control room decisions.

3. Greater explainability of AI-based forecasts to support confidence, transparency, and operational usability.

4. More efficient allocation and dispatch of flexibility in the Balancing Mechanism, reducing the risk of inefficient or reversed actions.

5. A foundation for improved coordination of flexibility with Distribution System Operators as network complexity increases.

Method(s)

Volta LRTP project will be delivered through four work packages. The approach is designed to commence with developing a high spatial resolution and high cadence forecasting capability, through to demonstrating scalable forecasting, then integrating and visualising operational explainability and finally developing an agentic AI framework. This phased approach reduces delivery risk by proving the value of the methodology before any decision is made on full-scale implementation or integration into NESO systems.

Work Package 1: Data

Description:

Establish the availability, quality and suitability of raw GSP-level metered data for high-granularity locational forecasting.

Methods / approach:

Work with NESO SMEs through workshops to review data sources, assess data quality, agree cleaning methods, address missing data, and remove the impact of NESO actions and NIV chasing from historic data where possible.

Output:

A validated and documented data foundation, including agreed data cleaning methods, treatment of missing data, and adjusted historic datasets suitable for model development.

Expected outcome:

Improved confidence that the forecasting model is trained on reliable, representative and operationally relevant data.

Work Package 2: Forecasting Model

Description:

Develop a scalable modelling framework for accurate locational forecasting across multiple network nodes.

Methods / approach:

Evaluate state-of-the-art deep learning approaches, including TFT, single-node univariate models, clustered models, globally pooled models, clustered multivariate models and pretrained foundation models, assessing the trade-off between accuracy, scalability and computational cost.

Output:

A proof-of-concept forecasting model using the best-performing approach, supported by evidence on model performance and scalability.

Expected outcome:

A scalable forecasting capability that can support high-resolution locational forecasts and provide a pathway for future operational integration.

Work Package 3: Explainability

Description:

Improve transparency and interpretability of the forecasting model so outputs can be understood and trusted by Control Room users.

Methods / approach:

Investigate explainability techniques such as DeepSHAP and Integrated Gradients, assess how forecasts interact with wider forecasting, network power flow and optimal dispatch tools, and review the potential role of agentic AI as an explainer and decision support tool.

Output:

Explainability outputs within the proof-of-concept, alongside a desk-based review of agentic AI use cases, implementation requirements and digital security considerations

Expected outcome:

Greater operator confidence, improved situational awareness and more informed decision-making based on transparent AI-enabled forecasts.

Work Package 4: Evaluation

Description:

Assess whether the model is operationally useful, technically robust and suitable for further development or future integration.

Methods / approach:

Hold workshops to identify user needs and use cases, agree an evaluation framework, and assess the model against metrics such as accuracy, inference time, training time, computational cost, transparency, scalability and usability.

Output:

An agreed evaluation framework and assessment of model performance against operational and technical criteria.

Expected outcome:

Clear evidence of whether the model delivers operational value and whether it should progress to further development, rollout or integration.

Measurement Quality Statement

Project outcomes will be measured through a combination of modelling, analysis, simulation and user evaluation. Forecasting performance will be assessed by comparing model outputs against historic and held-out GSP-level metered data using agreed accuracy metrics, forecast error measures, inference and training time, computational cost, scalability and transparency. Simulation or offline operational analysis may be used to test how improved locational forecasts could support earlier identification of constraint risks, more efficient reserve allocation and improved dispatch decisions compared with existing approaches.

Results will be validated through an agreed evaluation framework developed with NESO SMEs and Control Room users. This will include benchmarking the proof-of-concept model against current forecasting methods, testing performance across different time horizons, network locations and operating conditions, and reviewing explainability outputs with users to assess whether the forecasts are understandable and operationally useful. Workshop feedback will be used to validate whether the model outputs meet user needs and provide sufficient confidence to support future integration, rollout or further development.

Known limitations and uncertainties include the availability, completeness and quality of historic GSP-level data, the ability to fully remove the impact of NESO actions, and the extent to which offline analysis can represent real-time Control Room decision-making. The quantified benefits may therefore be indicative rather than definitive at proof-of-concept stage, with financial and operational benefits requiring further validation through phased rollout, live trial, operational integration and continued model monitoring.

Data Quality Statement

The project will use historic raw metered data at Grid Supply Point level as the core dataset for developing and evaluating locational forecasting models. This data will be reviewed with NESO subject matter experts to confirm its source, availability, coverage, quality and suitability for high-granularity forecasting. Settlement data available from Elexon may also be used to complement operational GSP metering. Where relevant, supporting operational data may also be considered to help distinguish underlying demand patterns from the effect of NESO actions, Balancing Mechanism activity and NIV chasing. Additional modelling inputs may include weather forecasts, electricity prices, network topology, socioeconomic indicators and other relevant datasets.

The reliability and completeness of the data will be assessed during the Data work package. Known areas of focus include missing or incomplete records, inconsistent metering quality, temporal or spatial gaps, and historic data that may be distorted by operational interventions or market actions. Appropriate cleaning methods will be agreed where possible, and modelling approaches will be designed to improve robustness where missing or imperfect data cannot be fully resolved.

In line with the ENA's ENIP document, the risk rating is scored 6 (low).

TRL Steps = 2 (3 TRL Steps)

Cost = 1 (£640k)

Suppliers = 1 (1 supplier)

Data Assumptions = 2 (Assumptions known but will be defined within project)

Total = 6 (Low)

Scope

Volta LRTP project scope covers the development and evaluation of a proof-of-concept, spatially resolved forecasting capability for Control Room decision support. In scope are the review and preparation of high-granularity GSP-level metered demand and supply data, the testing of scalable deep-learning forecasting approaches across multiple network nodes, and the development of a forecasting architecture that builds on the existing Volta Real Time Predictor capability. The scope also includes applying machine learning explainability techniques within a basic dashboard environment, assessing how forecasts can support operator understanding, and carrying out desk-based scoping of agentic AI opportunities for future innovation.

The project will develop a **proof-of-concept forecasting model** that can scale across hundreds of network nodes. The project will also test explainability tools in a basic dashboard and assess future opportunities for agentic AI.

Out of scope

The project will not convert data-cleaning, forecasting or explainability proofs of concept into production systems. Deployment, operational support and integration into business-as-usual activities are excluded.

It will not conduct exhaustive model screening or detailed hyperparameter tuning. Agentic AI is limited to desk-based research; developing, testing or deploying agentic AI models is not included.

Objective(s)

The objective of this project is to:

> Develop a high spatial resolution, high cadence forecasting capability
Develop and evaluate a deep learning probabilistic forecasting model capable of producing forecasts at high spatial (e.g. GSP) and temporal (sub-10-minute) resolution with high cadence for a single network node using curated historical data. Performance will be characterised using an agreed evaluation framework.

> Demonstrate scalable forecasting
Develop and evaluate scalable approaches for extending deep learning forecasting from a single node to hundreds of network nodes, assessing computational cost, training and inference time, robustness to limited historical data, and forecast performance against existing forecasting approaches.

>Integrate and visualise operational explainability
Develop a proof-of-concept forecast that incorporates fast feature-attribution and explainability methods to support operational decision making with a consistent forecast across both scheduling and energy forecasting timeframes.

>Develop an AI framework
Develop a framework describing potential applications of agentic AI within future control room forecasting operations, including use cases, technical requirements, governance considerations, and the opportunity to improve the transparency and usability of high-resolution forecasting.

Consumer Vulnerability Impact Assessment

This project has been assessed as having a neutral impact on customers in vulnerable situations because the outputs of this project are focused on providing improvements to the real time operation of the GB electricity network.

Success Criteria

D1.1: Data Availability and Quality Review

Output: Report reviewing the availability, coverage and quality of datasets required for high-resolution demand forecasting at GSP level, including recommendations for data cleaning, treatment of missing data, and model robustness.

Success Measures:

1.Completeness of data assessment
2.Identification of key data quality issues
3.Practicality of recommended data preparation strategy

Success Criteria:

Report delivered to NESO documenting available datasets, identified limitations and agreed recommendations for data preparation.

D2.1: Initial Spatially Resolved Forecasting Proof of Concept

Output: Initial proof-of-concept repository containing data ingestion, preprocessing and baseline probabilistic forecasting capability for a representative GSP, including example notebooks demonstrating approach to imperfect operational data.

Success measures:

1.Successful execution of data pipeline
2.Successful implementation of high cadence baseline forecast at GSP level using DL method

3.Documentation of modelling workflow.

Success criteria:

Source code and example notebook delivered to NESO, with reproducible execution on example nodes and datasets.

D2.2: Scalable Spatially Resolved Forecasting Proof of Concept

Output: Proof-of-concept forecasting framework demonstrating forecasting across multiple network nodes, including source code, configuration and evaluation of alternative approaches for scaling.

Success measure:

1.Completion of comparative evaluation of model architectures and approaches (single forecasting model for all GSPs or multiple models)
2.Successful implementation of a high spatial granularity high cadence forecast
3.Reproducibility of selected approach

Success criteria:

Repository containing evaluated forecasting scripts, documented evaluation of accuracy and performance, and proof-of-concept demonstrated to NESO.

D3.1: Explainable Forecasting Proof of Concept

Output: Proof-of-concept forecasting pipeline incorporating computationally efficient explainability methods (e.g. feature attribution) suitable for operational forecasting and decision support.

Success measure:

1.Successful integration of explainability methods
2.Computational performance capable of operating at forecast cadence
3.Usability of explanations for operational interpretation

Success criteria:

Proof-of-concept demonstrated to NESO showing forecast outputs together with explainability information, supported by documentation describing implementation and computational performance.

D3.2: Framework for Agentic AI Explainability and Decision Support

Output: Desk-based report describing opportunities for applying agentic AI to forecasting explainability and control-room decision support, including use cases, implementation requirements, governance, cyber security and future development roadmap.

Success measure:

1.Completeness of identified use cases
2.Practicality of implementation
3.Stakeholder relevance

Success criteria:

Report delivered to NESO identifying candidate applications, implementation considerations and recommendations for future innovation activity.

D4.1: Evaluation Framework and User Requirements

Output: Report documenting current and future user requirements, required spatial and temporal granularity, and an agreed evaluation framework covering forecast accuracy, computational performance, explainability and operational suitability.

Success measures:

1.Agreement on evaluation methodology
2.Completeness of performance metrics
3.Traceability to operational requirements

Success criteria:

Evaluation framework developed based on workshops with NESO SMEs, providing the basis for objective assessment of project outputs

D4.2 Final Forecasting Model Evaluation Report

Output: Final report evaluating the proof-of-concept forecasting approaches against the evaluation framework and documenting recommendations for implementation and future development.

Success measures:

1.Completeness of technical evaluation
2.Comparison of model architectures
3.Clarity of implementation recommendations.

Success criteria:

Final report delivered to NESO demonstrating evaluation against the evaluation framework and providing evidence-based recommendations for future implementation.

Project Partners and External Funding

University of Oxford. No external funding

Potential for New Learning

The project aims to develop new knowledge on how advanced deep-learning forecasting methods can be scaled from national-level forecasting to high-spatial-granularity forecasting across multiple network nodes. It will generate evidence on the relative performance, scalability and computational efficiency of different modelling approaches, including single-node, clustered, pooled, multivariate and pretrained foundation model options. The project will also develop innovation around the use of explainability techniques for operational forecasting, helping to identify which model drivers are most useful to Control Room users and how transparent AI-enabled forecasts can support situational awareness and decision-making.

Further innovation will come from testing how spatially resolved forecasts can be presented within a proof-of-concept dashboard environment and how they could integrate with wider forecasting, network power flow and optimal dispatch tools. The desk-based review of agentic AI will also identify potential future use cases for AI-enabled explanation and decision support, including implementation requirements and digital security considerations.

Sharing Findings with Industry

Findings will be shared with the wider industry through appropriate knowledge dissemination activities, which may include stakeholder workshops, technical briefings, project outputs, final reports and lessons learned summaries. Engagement with NESO SMEs, Control Room users, DSOs and other relevant industry stakeholders will help ensure that the learning is practical, transferable and aligned with operational needs. Where appropriate, outputs may also be shared through innovation forums, industry working groups, publications or conference presentations to support wider adoption of the project learning across the electricity sector.

At the end of the project, the project learning, including recommended next steps will be available on the ENA Smarter Network Portal.

Scale of Project

This development project will be conducted over a 12 month period by Oxford University in close collaboration with the NESO control

room, product owners, business analysts and market participants.

Technology Readiness at Start

TRL3 Proof of Concept

Technology Readiness at End

TRL6 Large Scale

Geographical Area

Will be based upon the GB NESO area of operations

Revenue Allowed for the RIIO Settlement

N/A

Indicative Total NIA Project Expenditure

Project spent broken down by work package:

- Deliverable1.1 - Data Availability and Quality review - £62,354
- Deliverable2.1 – Initial Spatially resolved forecasting proof of concept - £62,354
- Deliverable2.2 – Scalable spatially resolved forecasting proof of concept - £62,354
- Deliverable3.1 – Explainable forecasting proof of concept - £62,354
- Deliverable3.2 – Framework for Agent: AI explainability and decision support - £62,354
- Deliverable4.1 – Evaluation framework and user requirements - £187,064
- Deliverable4.2 – Final forecasting model evaluation report - £124,710

Total estimated project cost £640,000

The costs presented by work package reflect the direct project delivery activities. In accordance with the NIA Governance and Licence Condition requirements (including the provision for up to 25% of project costs for internal expenditure), the total reported project cost may differ from the sum of work package costs outlined above. All costs are reported to Ofgem in full through formal regulatory reporting at the end of each financial year.

Project Eligibility Assessment Part 1

Requirement 1

Facilitate the energy system transition and/or benefit consumers in vulnerable situations

Please answer **at least one** of the following:

How the Project has the potential to facilitate the energy system transition:

The project has the potential to facilitate the energy system transition by improving the accuracy, granularity and explainability of locational forecasting as the electricity network becomes more decentralised, variable and complex. Better visibility of demand, generation and network constraints at local levels can help Control Room operators make more informed decisions, support more efficient use of flexibility, and reduce reliance on inefficient redispatch or conservative operational margins.

By supporting improved coordination between NESO, Distribution System Operators, flexibility providers and market participants, the project could help enable more effective integration of distributed energy resources, demand-side flexibility and low-carbon technologies. This would contribute to a more resilient, data-driven and efficient whole-system operation, helping the industry manage increasing renewable variability while maintaining security of supply and supporting better cost outcomes for consumers.

How the Project has potential to benefit consumer in vulnerable situations:

N/A

Requirement 2 / 2b

Has the potential to deliver net benefits to consumers

Project must have the potential to deliver a Solution that delivers a net benefit to consumers of the Gas Transporter and/or Electricity Transmission or Electricity Distribution licensee, as the context requires. This could include delivering a Solution at a lower cost than the most efficient Method currently in use on the GB Gas Transportation System, the Gas Transporter's and/or Electricity Transmission or Electricity Distribution licensee's network, or wider benefits, such as social or environmental.

Please provide an estimate of the saving if the Problem is solved

n/a

Please provide a calculation and/or description of the expected benefits of the solution

The expected benefits of the solution are primarily linked to improved forecasting accuracy, better operational decision-making and reduced balancing inefficiency. Given that redispatch between network zones contributes approximately £1.7bn to NESO balancing costs, even a small improvement in forecasting and dispatch efficiency could represent material value. An illustrative 1% reduction would equate to approximately £17m per year, while a 0.5% reduction would equate to approximately £8.5m per year. These figures are indicative and would need to be validated through model performance testing, operational simulation and comparison with existing forecasting approaches.

The wider benefits include improved Control Room visibility, earlier identification of constraint risks, more efficient reserve allocation, better coordination with DSOs and flexibility providers, improved confidence in AI-enabled forecasts, and potential long-term consumer value through lower whole-system costs.

Please provide an estimate of how replicable the Method is across GB

The method could be replicable to distribution networks in GB, provided that comparable network-node-level data is available and of sufficient quality. However, the highly meshed characteristics of distribution networks may require separate methodologies to achieve comparable accuracy.

Please provide an outline of the costs of rolling out the Method across GB.

Rolling out the method to other networks would involve costs associated with data access and preparation, model scaling, cloud or compute infrastructure, system integration, model experimentation/validation, user engagement, training, governance, and ongoing support.

Requirement 3 / 1

Involve Research, Development or Demonstration

Projects must have the potential to have a Direct Impact on a Network Licensee's network or the operations of the System Operator and involve the Research, Development, or Demonstration of at least one of the following (please tick which applies):

☐ A specific piece of new (i.e. unproven in GB, or where a method has been trialled outside GB the Network Licensee must justify repeating it as part of a project) equipment (including control and communications system software).

☐ A specific novel arrangement or application of existing licensee equipment (including control and/or communications systems and/or software)

☐ A specific novel operational practice directly related to the operation of the Network Licensees system

☐ A specific novel commercial arrangement

Involve Research, Development or Demonstration - Please select all that apply

☐ A specific piece of new equipment (including monitoring, control and communications systems and software)

☑ A specific piece of new technology (including analysis and modelling systems or software), in relation to which the Method is unproven

☑ A new methodology (including the identification of specific new procedures or techniques used to identify, select, process, and analyse information)

☐ A specific novel arrangement or application of existing gas transportation, electricity transmission or electricity distribution equipment, technology or methodology

☐ A specific novel operational practice directly related to the operation of the GB Gas Transportation System, electricity transmission or electricity distribution

☐ A specific novel commercial arrangement

Specific Requirements 4 / 2a

Please explain how the learning that will be generated could be used by the relevant Network Licensees

Relevant Network Licensees (e.g. DNOs/DSOs) could use the learning from this project to assess how scalable, spatially resolved forecasting methods could be applied across their own networks to improve visibility of local demand, generation and constraint risks. The findings on data quality, model architecture, scalability, explainability and evaluation metrics would help licensees understand the practical requirements for adopting similar forecasting approaches, including data preparation, local calibration, integration with existing planning and operational systems, and user adoption. This learning could support improved network planning, flexibility coordination, constraint management and whole-system operation, helping licensees make better-informed decisions as the electricity system becomes more decentralised, variable and low carbon.

n/a

Is the default IPR position being applied?

☑ Yes

Project Eligibility Assessment Part 2

Not lead to unnecessary duplication

A Project must not lead to unnecessary duplication of any other Project, including but not limited to IFI, LCNF, NIA, NIC or SIF projects already registered, being carried out or completed. Networks must explicitly mention similar projects that they have considered and how these differ.

Please demonstrate below that no unnecessary duplication will occur as a result of the Project.

The project can demonstrate that no unnecessary duplication will occur because it is designed to build on, extend and operationalise existing learning from the NIA Volta: Real Time Predictor project, rather than recreate previous work.

NIA Volta: Real Time Predictions NIA2_NESO105: this predecessor project was focused on developing novel high-resolution forecasting methods for national demand. By contrast, this phase is specifically targeted towards regional (GSP) demand forecasting. Applying the same methodology out-of-the-box is not expected to succeed given known data quality issues with GSPs and the

requirement for spatial resolution between network nodes.

GSP Modelling NIA_SHET_0058: This project focuses on transmission network modelling rather than load forecasts.

If applicable, justify why you are undertaking a Project similar to those being carried out by any other Network Licensees.

N/A

Additional Governance And Document Upload

Please identify why the project is innovative and has not been tried before

Volta LRTP project is innovative in its use of advanced AI to provide high-resolution, spatially coherent forecasts for network nodes. This requires processing large amounts of data, with known complexities including network switching causing regime changes. The proposed methodology will be a major advancement on methods currently undertaken by NESO. The project will investigate state-of-the-art approaches, including using global forecasting methods to produce forecasts for multiple GSPs in a single pass. The project will test new modelling architectures, compare scalability and accuracy trade-offs, address data limitations such as missing data and operational distortions, and explore explainability techniques and agentic AI as tools for operational trust and decision support. This combination of high-resolution forecasting, scalable AI modelling, operator explainability and potential integration with dispatch decision-making represents new learning for NESO and the wider electricity industry.

Relevant Foreground IPR

The project is expected to generate Relevant Foreground IPR in the form of new learning, methodologies, model evaluation outputs and proof-of-concept artefacts relating to high-granularity locational forecasting. This may include evidence on the suitability and scalability of different forecasting model architectures, data cleaning and preparation approaches for GSP-level metered data, methods for handling missing or distorted data, evaluation frameworks, explainability outputs, dashboard concepts, and learning on the potential use of agentic AI as an explainer or decision support tool.

Relevant Foreground IPR may also include project reports, technical documentation, model performance assessments, lessons learned, requirements for future operational integration, and recommendations for further development or rollout across Great Britain. The foreground learning is expected to be valuable to NESO, Network Licensees and the wider electricity industry because it will provide practical evidence on how advanced AI forecasting can be scaled, explained and assessed for operational use.

Use of some Relevant Foreground IPR may rely on Background IPR, including existing Volta Real Time Predictor learning, previously developed forecasting approaches, existing NESO data sources, internal operational processes, and any third-party or open-source modelling tools used during development. Where Background IPR is required, appropriate access, licensing and usage rights would need to be confirmed to ensure that the Relevant Foreground IPR can be used, shared or further developed in accordance with project governance and intellectual property arrangements.

Data Access Details

Data for this project and all other projects funded under the Network Innovation Allowance (NIA), or Strategic Innovation Fund (SIF) can be found or requested in a number of ways:

1. A request for information via the Smarter Networks Portal at https://smarter.energynetworks.org, to contact select a project and click ‘Contact Lead Network’. National Energy System Operator already publishes much of the data arising from our innovation projects here so you may wish to check this website before making an application.
2. Via our Innovation website at https://www.neso.energy/about/innovation
3. Via our managed mailbox innovation@neso.energy

Details on the terms on which such data will be made available by National Energy System Operator can be found on our website: Data Sharing Approach | National Energy System Operator.

Please identify why the Network Licensees will not fund the project as a part of it's business and usual activities

The project would not typically be funded by NESO as part of business-as-usual activities because it involves the development and testing of new forecasting methods that have not yet been proven for high-granularity, spatially resolved operational use. BAU funding is generally focused on established, lower-risk activities required to operate, maintain and plan the network, whereas this project

involves innovation risk, including uncertainty around data quality, model scalability, explainability, integration requirements and the extent of future operational benefits.

Please identify why the project can only be undertaken with the support of the NIA, including reference to the specific risks (e.g. commercial, technical, operational or regulatory) associated with the project

The project requires NIA support because it involves the development, testing and evaluation of an unproven method for high-granularity, spatially resolved forecasting that carries significant technical, operational, commercial and regulatory uncertainty. The technical risks include uncertainty around GSP-level data quality, missing data, model scalability across hundreds of network nodes, forecast accuracy, computational cost and the effectiveness of explainability methods for deep-learning outputs. Operational risks include whether the model outputs can be trusted by Control Room users, integrated with existing forecasting, power flow and dispatch processes, and used effectively in real-time decision-making. Commercial risks include uncertainty over the scale and timing of benefits, the cost of future rollout, supplier or platform dependencies, and whether the approach will deliver sufficient value to justify wider deployment. Regulatory and governance risks include data access, cyber security, model assurance, transparency, auditability and the need for any future policy or process changes before operational adoption.

NIA support is therefore needed to de-risk the method, generate transferable learning for Network Licensees and the wider industry, and provide evidence on whether the solution can be technically, operationally and commercially justified before any future business-as-usual rollout or full-scale deployment.

This project has been approved by a senior member of staff

- [x] Yes