IBM

nationalgridESO

Input Data Model Report

Advanced Dispatch Optimiser – Phase 2

NIA2_NGESO044

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1 Introduction

This document acts as the *Data model report* deliverable specified in the Advanced Dispatch Optimiser – Phase 2 (NIA2_NGESO044) project agreement between National Grid Electricity System Operator Limited (ESO) and IBM United Kingdom Limited.

This report builds on work previously completed by Google X's Tapestry project. As such it is suggested that Tapestry's Advanced Dispatch Optimizer System Roadmap Report is read in advance of this.

The core output of the Google X Tapestry report was the below architectural overview of the proposed dispatch system:

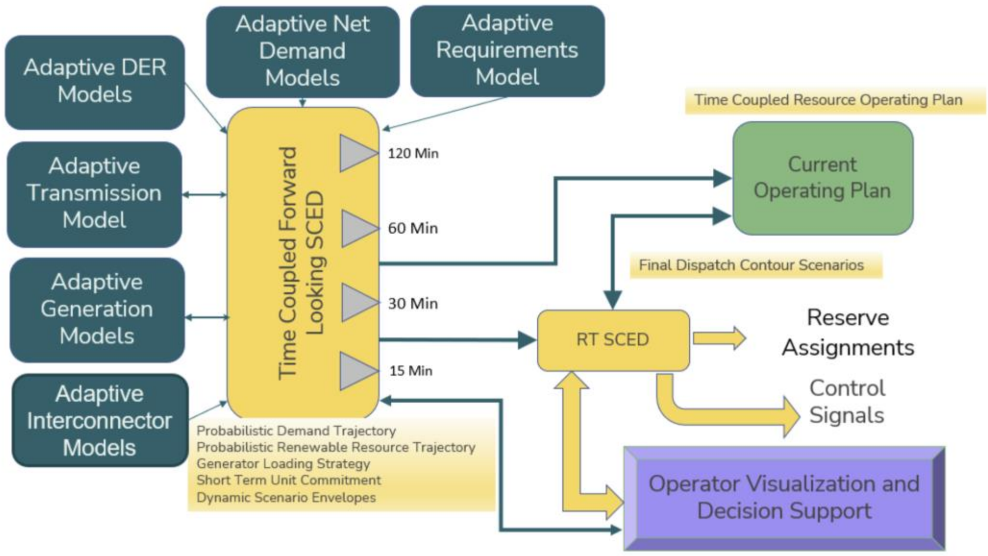


Figure 1: Google X Tapestry's Advanced Dispatch Optimizer System Roadmap Report – Architectural Overview

Within this *Data model report* deliverable, the focus is on the Adaptive Input Data Models[1] – exploring current and planned capabilities, the required final capability, as well as the associated gaps and next steps. The model groups discussed are:

1. **Adaptive Generation Models[2]**
    a. Thermal
    b. Renewable
    c. Grid scale duration limited assets, such as batteries and pumped storage [added following Google X clarification and not explicitly referenced within the Tapestry report]

[1] Whilst Google X explicitly reference the "*period from four hours ahead through to real-time dispatch operations*", the detailed vision in this report is purposefully time horizon-agnostic – providing an element of flexibility when considering the optimal use of such models.
[2] These generation models are designed at a high-level to be applicable to any fuel type participating in the balancing mechanism. However, given the dynamic nature of the energy sector, one would have to ensure going forward that no new technologies or fuel types are mistakenly omitted.

2. Adaptive Transmission Model
3. Adaptive Interconnector Models
4. Adaptive Distributed Energy Resources (DER) Models
5. Adaptive Net Demand Models
    a. Demand Forecast and Consumer Behaviour
    b. Embedded DER

[Note: The Adaptive Requirements Model is out of scope for this engagement.]

An important clarification here is the distinction between DER and embedded DER. For purposes of this report, definitions are as follows:

- DER = Instructible, distribution-level generation resources, modelled either as individual units or aggregated resources.
- Embedded DER = Non-instructible resources without any operational metering visible to ESO. ["Behind-the-meter" (BTM) resources.]

The positioning of each of these model groups within the wider UK electricity landscape is indicated in the below graphic.

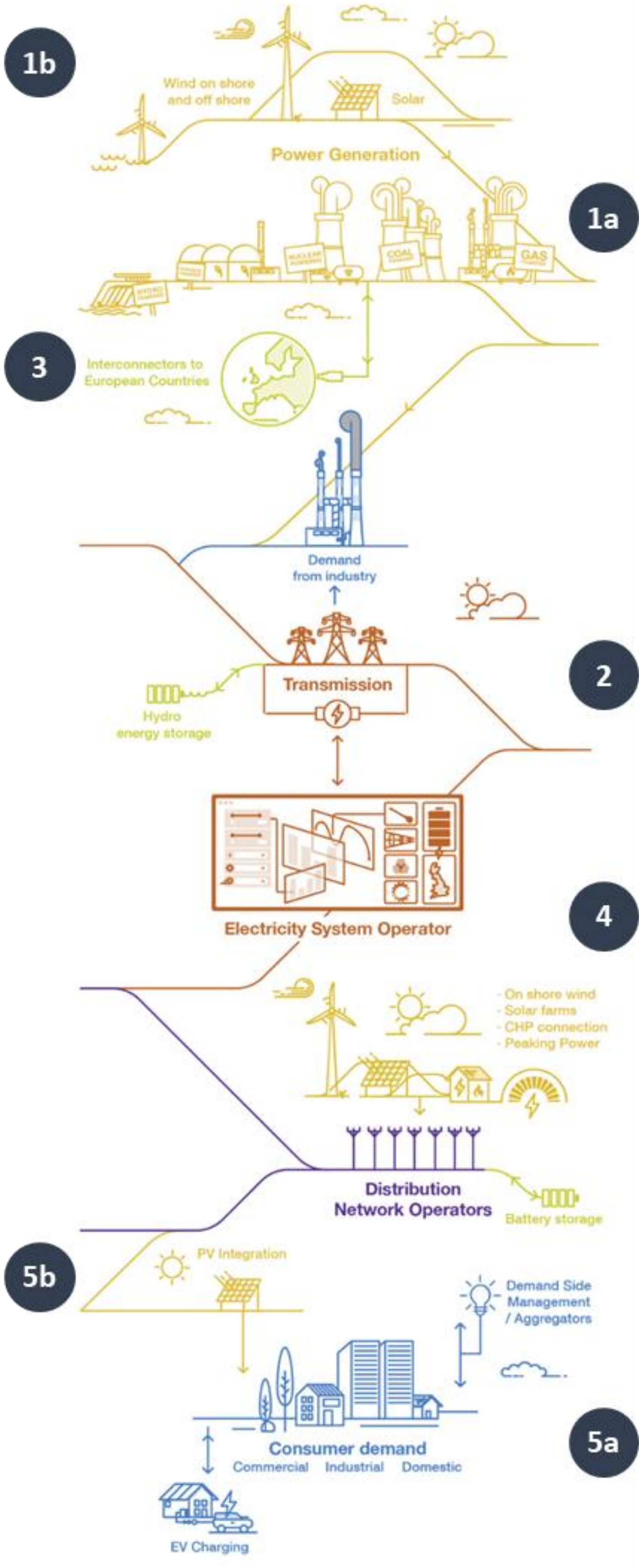


Figure 2: Model group positioning and focus within the context of the wider UK electricity landscape

1.1 Discussion Point: Use of Existing External Models and Procedures

Whilst the primary purpose of this report is to further detail the proposed input data model groups outlined by Google X Tapestry (see figure above), it is also worth noting concerns raised by ESO Subject Matter Experts (SMEs) regarding the inward-looking nature of the end vision.

The end vision, at a high-level, describes a set of internal ESO capabilities. Given the interconnected and interoperating model vision outlined at the core of the Virtual Energy System (VES), one may expect the future dispatch plan to focus more on the potential value that can be brought by parties external to ESO. For example, focus could be on gaining access and integrating existing transmission models initially, as opposed to defining a new adaptive ESO-owned model. Additionally, in-flight projects such as CrowdFlex may succeed in getting suppliers / aggregators to provide ESO with access to their data in some form.

This view is not seen as being directly in opposition with the IBM interpretation of the Google X end vision, with certain elements rightly owned by external parties. This principle is alluded to below when discussing, for example, the Transmission Operator (TO) ownership of dynamic line rating calculations, or the Distribution System Operator (DSO) ownership of Distributed Energy Resource (DER) models.

Full analysis of existing capabilities external to ESO is not in scope for this engagement, but relevant elements are considered at a high-level and highlighted as necessary deep-dive discussions in the roadmap.

1.2 Discussion Point: Forecasting and Scenario Testing

An important principle in this report is the use of forecasting models and subsequent scenario testing as connected capabilities. Within the Google X end vision, there are multiple references to scenario testing capabilities, with the input data models able to support variable inputs to assess the associated sensitivity of outputs.

It is important to note, responding to a clarification request, that all proposed models look to forecast an output of some type. Differences lie in the proposed use of existing forecast data when detailing the model inputs. For example, in Google X's view of predicting actual demand, it is suggested that existing demand forecasts could be used as input data, with the model then assessing how specific scenario conditions may alter this forecast in reality. In this case, a separate forecast model (be that existing or new) is a core dependency.

However, the detailed methodologies can readily be altered to not include any such forecast dependencies – with the adaptive input data models instead performing a straight forecasting function (as opposed to assessing and altering existing forecasts), with an additional scenario testing capability[3].

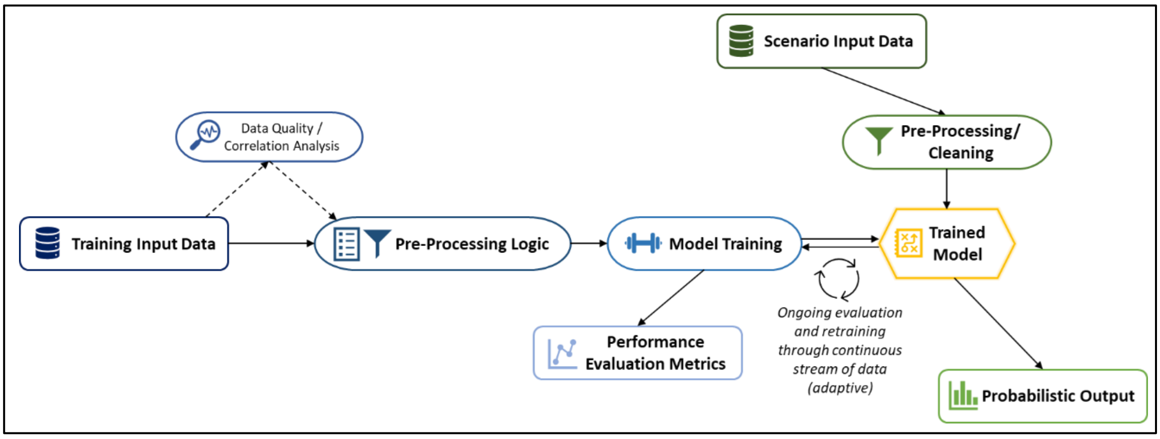
[3] Note: The architectural deliverable discusses how an overall scenario testing capability could work in principle – appreciating the need for consistency across input models, as well as highlighting points for consideration.

2 Executive Summary

This report details the adaptive input data model groups proposed by Google X, namely: Generation, Transmission, Interconnector, DER, and Net Demand (split into actual demand and embedded DER modules).

Headlines

- With the exception of Transmission, all model areas have the same high-level process architecture – training a predictive supervised learning model, with an ongoing evaluation and retraining element, to enable testing of scenarios.



- Creating a new "IBM View", the Transmission models are defined by constraint problem type (e.g., Thermal, Generator Stability, Voltage etc.) – analysing the value of optimiser-inclusion and acknowledging the nuanced differences in approach. The advised problem types for initial inclusion in the optimiser logic based on this analysis are: Thermal Constraints, Generator Stability, Voltage, and RoCoF / Inertia / Largest Loss.
- Data availability varies greatly by modelling area (see table below), though there are clear instances where multi-year data collection processes are necessary to meet the outlined historic data requirements.
- Data quality and granularity vary by input data source (see table below). For example, there are multiple known issues with Data Historian, but no anticipated issues with the Transmission model data (in part due to the sophistication of existing processes)[4].
- The important holistic view of model interconnectedness and management of scenarios can be found in the Architectural deliverable.
- Discussions around appropriate ownership of these modelling areas are raised throughout the report and reflected in the roadmap deliverable.

The high-level insights drawn from the series of adaptive input data models detailed in this report are highlighted in the below table.

[4] Note: data has not been able to be extracted for IBM-run data quality analysis. Comments instead reflect conversations had with ESO SMEs.

Table 1: High-Level Input Data Model Insights

<table>
<tr><th>End Vision Module</th><th>Input Data Model Area</th><th>Core Question</th><th>Data Requirements Headlines</th><th>Data Availability Headlines</th><th>Data Quality / Granularity Headlines</th></tr>
<tr><td rowspan="2">Adaptive Input Data Models</td><td>Generation</td><td>Given a set of dispatch instructions to test, combined with forecast input data such as weather, likely maintenance etc., what is the predicted actual MW output for a specified generator?</td><td><u>Historic Training Data</u>
- Generator Offer Data
- Production Forecast Data
- Instructed MW output
- Actual MW output
- Weather
- Generator Conditions
- Total System Demand
- Binding Transmission Constraints
- Dispatch State
<u>Scenario Input Data (Forward-Looking)</u>
- Theoretical Dispatch Instructions
- Existing PNs for given period
- Generator Offer Data
- Weather
- Etc. as above</td><td>• Approx. 3 years of data collection in real time necessary to meet the historic “Additional Information” data requirements.
• Data groups required for scenario testing are generally more available, and hence not as restrictive to model development as the training data.</td><td><u>Data Historian Issues</u>
• Muddled data timestamps.
• No differentiation between out-of-service and decommissioned.
• Incorrect flow direction.
• Untrustworthy static generator data.
• Slow data extraction.
• Potential sunsetting.
Lack of data dictionary for Data Historian and National Grid Economic Database (NED).</td></tr>
<tr><td>Transmission (IBM View)</td><td>Split by constraint problem type (e.g., thermal, generator stability, voltage etc.), what are the forecasted transmission constraints to be fed into the optimiser module?</td><td>For the identified constraint problem types (Thermal, Generator Stability, Voltage, Rate of Change of Frequency / Inertia / Largest Loss),
- Local Network Characteristics
- (Dynamic) Line Ratings
- Generator Characteristics
- Network Model
- Fault Understanding
- Contract Information
- Weather
- Network Configuration
- Generation, Demand, and Interconnector Forecasts
- System Operating Plans
- Faults
- Voltage Profile
- Largest Demand Loss
- Largest Generation Loss</td><td>• Not subject to the historic data availability issues observed in other areas.
• No significant data availability issues anticipated.[5]</td><td>• No known significant data quality issues.
• Unknown factors for consideration include: the agreed quality and granularity of any TO-produced dynamic line rating data, and accuracy / granularity of current weather forecasts for scenario building.</td></tr>
</table>

[5] Whilst there may be availability issues with, for example, network sensor data in the TO-owned calculation of dynamic line ratings, these would be observed by ESO through the quality / granularity of said ratings – see unknown factors for consideration comment.

	Interconnector	*Given a prescribed set of forecasted scenario conditions, what is the forecasted actual flow on the interconnectors (prior to any further required reactive manual trading / intervention post-optimiser run)?*	Historic Training Data - Scheduled interconnector flow trends - Actual interconnector flow trends - GB Market Data - Foreign Market Data Scenario Input Data (Forward-Looking) - Real-time power flows on transmission interconnectors - Scheduled interconnector flow trends - GB Market Data - Foreign Market Data	• Most elements of the historic training data are available in some form (perhaps requiring purchase). • Whilst some variables are readily available, the limited forecasting of market conditions may lead to difficulty in defining relevant, accurate scenarios.	• Actual interconnector flow of good quality / granularity. • Forecasted market data considered poor quality and accuracy. Further Considerations • Granularity of historic scheduled flows. • Usability of historic market data.
	DER	*Given a set of dispatch instructions to test, combined with forecast input data such as weather, likely maintenance etc., what is the predicted actual MW output for a specified resource / aggregated resource group?*	Historic Training Data - DER / DER Group Offer Data - Production Forecast Data - Instructed MW output - Actual MW output - Weather - Resource Conditions - Total System Demand - Binding Transmission Constraints - Dispatch State Scenario Input Data (Forward-Looking) - Theoretical Dispatch Instructions - Existing PNs for given period - DER / DER Group Offer Data - Weather - Etc. as above	• Approx. 3 years of data collection in real time necessary to meet the historic "Additional Information" data requirements. • Data groups required for scenario testing are generally more available, and hence not as restrictive to model development as the training data.	As for Generation above.
Net Demand Forecast Module[6]	Demand Forecast and Consumer Behaviour	*Given a set of fixed inputs (e.g., day of week, time of day etc.), combined with forecast input data such as weather, market prices etc., and the existing demand forecast,*	Historic Training Data - Demand Forecasts - Actual Demand - Demand Flexibility Service instructions - Weather - Market Prices	[Unable to obtain SME input.]	[Unable to obtain SME input.]

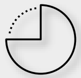
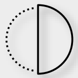
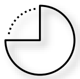
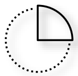
[6] Note that, with this view, demand modelling is split into actual (gross) demand and embedded DER, with net demand calculated as the difference between these values. This approach vs. direct modelling of net demand is discussed in section 6.1.

		what is the predicted actual demand at the chosen level of granularity?	Scenario Input Data (Forward-Looking) - Demand Forecasts - Demand Flexibility Service instructions - Weather - Market Prices		
	Embedded DER	*What is the amount and type of embedded DER at a given level of granularity, and what is the subsequent impact on net demand?*	Dependent on methodology – see discussion in section 6.4.	N/A	N/A

Distilling this information further to identify key data challenges and immediate actions:

Table 2: Data Challenges and Next Steps Summary

End Vision Module	Input Data Model Area	Key Data Challenges	Immediate Actions
Adaptive Input Data Models	Generation	*Availability* *Quality*	• Planning of real-time data collection period where required (e.g., generator conditions, total system demand, binding transmission constraints etc.). • Full analysis of quality and granularity issues (e.g., Data Historian, NED, weather data).
	Transmission (IBM View)	*Availability* *Quality*	• Discussion with TOs regarding the ownership, format, and required frequency of dynamic line ratings. • Full analysis of quality and granularity issues (e.g., accuracy / granularity of current weather forecasts for scenario building).

	Interconnector	*Availability*  *Quality* 	• Detailed analysis of data sources (some requiring purchase) to establish whether granularity and quality are sufficient for this purpose (e.g., timescales of “scheduled flows”, ability to forecast market data in the creation of scenarios).
	DER	*Availability*  *Quality* 	As for generation: • Planning of real-time data collection period where required (e.g., generator conditions, total system demand, binding transmission constraints etc.). • Full analysis of quality and granularity issues (e.g., Data Historian, NED, weather data).
Net Demand Forecast Module	**Demand Forecast and Consumer Behaviour**	[Unable to obtain SME input.]	• Initial availability and quality analysis (as completed for the other modelling areas).
	Embedded DER	Dependent on methodology – see discussion in section 6.4.	N/A

3 Regulatory Considerations, Explainable AI, and Process Impacts Overview

3.1 Explainable AI and Associated Regulatory Considerations

3.1.1 Overview

National Grid ESO's role within the UK's electricity landscape requires an inherent level of transparency and explain-ability. Acknowledgement of this responsibility was seen, for example, in the publication of datasets as part of the Forward Plan commitment to increase the transparency of the Balancing Mechanism operational decision making. These publications included a list of actions, explanations of the underlying reasons, as well as an overall process methodology document.

These areas become even more important as ESO shifts to increased levels of Artificial Intelligence (AI) adoption and AI augmented decision making. For example, one would need to be able to justify an AI-generated decision to not issue dispatch instructions to the lowest price unit (perhaps due to historical discrepancies between Bid Offer Data and actual performance). Considerations in this particular AI-generation area extend further to include contractual elements – e.g., should new market participants be informed of the various unit-level metrics feeding into the optimiser, and therefore determining their usage?

Whilst this section provides a high-level overview, and is included here for completeness, model-specific elements of Explainable AI will be further discussed in the relevant areas of section 5

Adaptive Input Data Models below.

3.1.2 Explainable AI Principles

The field of Explainable AI (XAI) is defined at a high-level as

"*a set of processes and methods that allows human users to comprehend and trust the results and output created by machine learning algorithms*".[7]

As further noted, "*Explainable AI is used to describe an AI model, its expected impact and potential biases. It helps characterize model accuracy, fairness, transparency and outcomes in AI-powered decision making. Explainable AI is crucial for an organization in building trust and confidence when putting AI models into production.*"

"*There are many advantages to understanding how an AI-enabled system has led to a specific output. Explain-ability can help developers ensure that the system is working as expected, it might be necessary to meet regulatory standards, or it might be important in allowing those affected by a decision to challenge or change that outcome.*"

With regards ESO, the necessity for XAI-style thinking covers all of the above listed points. It would enable any regulatory requirements to be met, as well as provide control room engineers with a clear view of the underlying reasoning so that they can take appropriate action.

3.1.3 Explainable AI Techniques

As detailed again by IBM,

"*The setup of XAI techniques consists of three main methods. Prediction accuracy and traceability address technology requirements while decision understanding addresses human needs. Explainable AI — especially explainable machine learning — will be essential if future* [*control room engineers*] *are to understand, appropriately trust, and effectively manage an emerging generation of artificially intelligent machine partners.*"

Exploring each of these in turn:

<u>Prediction Accuracy</u>

"*Accuracy is a key component of how successful the use of AI is in everyday operation. By running simulations and comparing XAI output to the results in the training data set, the prediction accuracy can be determined. The most popular technique used for this is Local Interpretable Model-Agnostic Explanations (LIME), which explains the prediction of classifiers by the ML algorithm.*"

<u>Traceability</u>

"*Traceability is another key technique for accomplishing XAI. This is achieved, for example, by limiting the way decisions can be made and setting up a narrower scope for ML rules and features. An example of a traceability XAI technique is DeepLIFT (Deep Learning Important*

[7] https://www.ibm.com/topics/explainable-ai

FeaTures), which compares the activation of each neuron to its reference neuron and shows a traceable link between each activated neuron and even shows dependencies between them."

Decision Understanding

"*This is the human factor. Many people have a distrust in AI, yet to work with it efficiently, they need to learn to trust it. This is accomplished by educating the team working with the AI so they can understand how and why the AI makes decisions.*"

Whilst all three of these methods are important and are inherently interconnected, as alluded to above, Decision Understanding is arguably the most critical for ESO.

3.1.4 Explainable AI Benefits

Whilst many of the benefits of XAI adoption are clear, they can be concisely summarised as:

1. **Operationalise AI with trust and confidence**
   Build trust in production AI. Rapidly bring your AI models to production. Ensure interpretability and explain-ability of AI models. Simplify the process of model evaluation while increasing model transparency and traceability.
2. **Speed time to AI results**
   Systematically monitor and manage models to optimise business outcomes. Continually evaluate and improve model performance. Fine-tune model development efforts based on continuous evaluation.
3. **Mitigate risk and cost of model governance**
   Keep your AI models explainable and transparent. Manage regulatory, compliance, risk and other requirements. Minimise overhead of manual inspection and costly errors. Mitigate risk of unintended bias.

3.2 Process and Responsibility Impacts

In reading the Google X *End Vision*[8], it is abundantly clear that implementation of an adaptive model architecture of this type would require significant changes to existing processes and employee responsibilities. As such, this should be a fundamental consideration in planning the speed and incremental approach for both development and business integration stages.

Indeed, as noted by an ESO Operational Manager in their assessment of the Google X report[9],

"*Moving to this kind of model is likely to impact most members of the Energy, Strategy and Transmission teams and many of their processes. This will be a different toolset and different process for the whole Energy team with different optimisation opportunities that will have to be learnt. The document does not mention scheduling process which is mainly*

[8] Google X Tapestry's *Advanced Dispatch Optimizer System Roadmap Report*
[9] *Virtual Energy System - Advanced Dispatch Optimiser Google X Comparison (April 2022)*

managed by the Strategy but they will likely be responsible for setting up the dispatch tools."

4 Adaptive Model Considerations, Advised Incremental Approach, and Cone of Uncertainty

4.1 Adaptive Models

4.1.1 High-Level Origin and Definition

The field of Adaptive Machine Learning (ML) was established to address the issue of "concept drift" – a phenomenon in which the underlying distributions of input data shift over time, resulting in altered relationships between the input and target variables. A traditional ML trained model would therefore become "out of date" in this case due to the underlying usage assumption that the training data remains generally representative of the wider population.

At a high level, adaptive ML models counter this issue through continuous adaption to rapidly changing data sets. As such, they are particularly well suited to real-time, real-world environments.

4.1.2 Definition within the ESO Context

At a slightly more technical level, the actual definition of adaptive ML may vary depending on use case. For purposes of this report, an adaptive ML model is defined as any model with a continuous improvement and automated retraining element. This may take the form of a supervised or unsupervised traditional ML model with ongoing retraining module built into the architecture, or a form of efficient reinforcement learning akin to a continuous learning trial-and-error approach.

4.1.3 Considerations

In considering use of an adaptive ML model, particularly comparatively to traditional ML with manual retraining, there are several points for consideration in answering the core question

"Is the costly development and deployment of an adaptive model worth it for the given problem?".

These considerations may include:

- the underlying data relationships,
- pace of concept drift,

[both looking at the *technical suitability of the problem*]

- associated incremental value gain.

[exploring the *business merit of development*]

4.1.3.1 Underlying Data "Structures"

An important consideration in deciding whether to develop an adaptive model is whether or not there is sufficient "structure" in the underlying data. By this, we are referring to the intrinsic relationships between the data variables that a ML model exploits to form its output.

Failing this "sufficient structure", in a resultant system of high entropy dynamics, the incremental value gain from implementing an adaptive-type model (as opposed to traditional ML or other processes) is low or non-existent. This is because the model, as expected, would be unable to accurately predict a system dictated by "significant randomness".

It is also worth noting that the perception of randomness within a system could be the result of missing core data sources. For example, if one were trying to predict GB nuclear power generation but only had temperatures in Australia as available data inputs, any defined relationship between data inputs and the target would appear arbitrary and inaccurate. The perception of the system dynamics would subsequently be one of "complete randomness".

4.1.3.2 Shifting of Data Distributions (Concept Drift)

As alluded to above in describing the origins of adaptive ML, a further consideration centres around the pace at which the underlying data relationships are changing. With fast changing data, adaptive models may well be ideal for the given use case. Conversely, if the data distributions are relatively stable, one may question the level of additional value gained from the likely long and expensive development and deployment of an adaptive model.

4.1.3.3 Emergence of New Significant Variables

Related to concept drift, drastic changes to the general environment could lead to the emergence of new vectors that impact the target variable. Whilst concept drift perhaps implicitly focuses on the movement of existing, known input parameters, this additional consideration describes a fundamental change / disruption to the dynamics of the system. As one might expect, these drastic changes are likely to be relatively infrequent and less of a concern when considering the use of an adaptive model. However, in a rapidly changing environment, this may present an issue.

4.1.3.4 Associated Incremental Value Gain

As mentioned, regardless of whether the problem suits an adaptive-type solution, the wider question of "*should the business implement such a solution?*" remains. Assuming there are no data issues such as those highlighted above, the answer to this is a function of incremental value, associated cost, and business requirement. As always, there is a balance to be struck between cost of development and value gain relative to business requirements. If, for example, more value would be gained from improving metering data than developing an adaptive model, money may be better spent there.

4.2 Advised Incremental Approach and Cone of Uncertainty

Again, we consider the key question

"Is the costly development and deployment of an adaptive model worth it for the given problem?".

The answer to this may obviously vary by individual input data model stream. To address the above considerations (particularly considering the level of upheaval that the adaptive vision presents to existing processes), an incremental stepwise approach is advised. Such a stepwise approach to the input data models would support continuous improvement, reduce the uncertainty around associated value at each stage, inform best next steps, and avoid regret spend.

Forming a view of this recommended approach, a useful visualisation depicting the principle is the "Cone of Uncertainty". By taking a stepwise approach, evaluating the business value at each stage, one can make a series of informed decisions as to:

1. whether the subsequent stage is worth undertaking (based upon likely incremental business value, suitability of data etc.),
2. what the most suitable definition / specification of said subsequent stage would be.

Conversely, if one were to jump immediately to the adaptive "final capability", there is currently a great degree of uncertainty surrounding the suitability of the problem, anticipated value gain, "correct" specification etc. This could result in significant regret spend (both time and monetary) if a much simpler solution would have produced comparable (or even better) results. The advised approach gradually removes this uncertainty.

Starting with development of a set of "Minimum Viable Models", the value relative to current processes can be quickly quantified (in terms of accuracy, ease of use etc.). Combining these results with the outcomes of a parallel data science workstream, this can inform the most important next steps of development.

4.2.1 Data Science Workstream

A data science workstream running in parallel to model development would aim to answer the considerations above regarding underlying data "structures", likely speed of concept drift / variable emergence, and associated model value. Activities may include detailed correlation analysis, historic data distribution drift and projected future drift analysis, model suitability study, and value calculation / approximation.

The outputs of this workstream would address the considerations above and inform decisions as to the most sensible next step of development – both in terms of next step definition, and next step go / no go decision making.

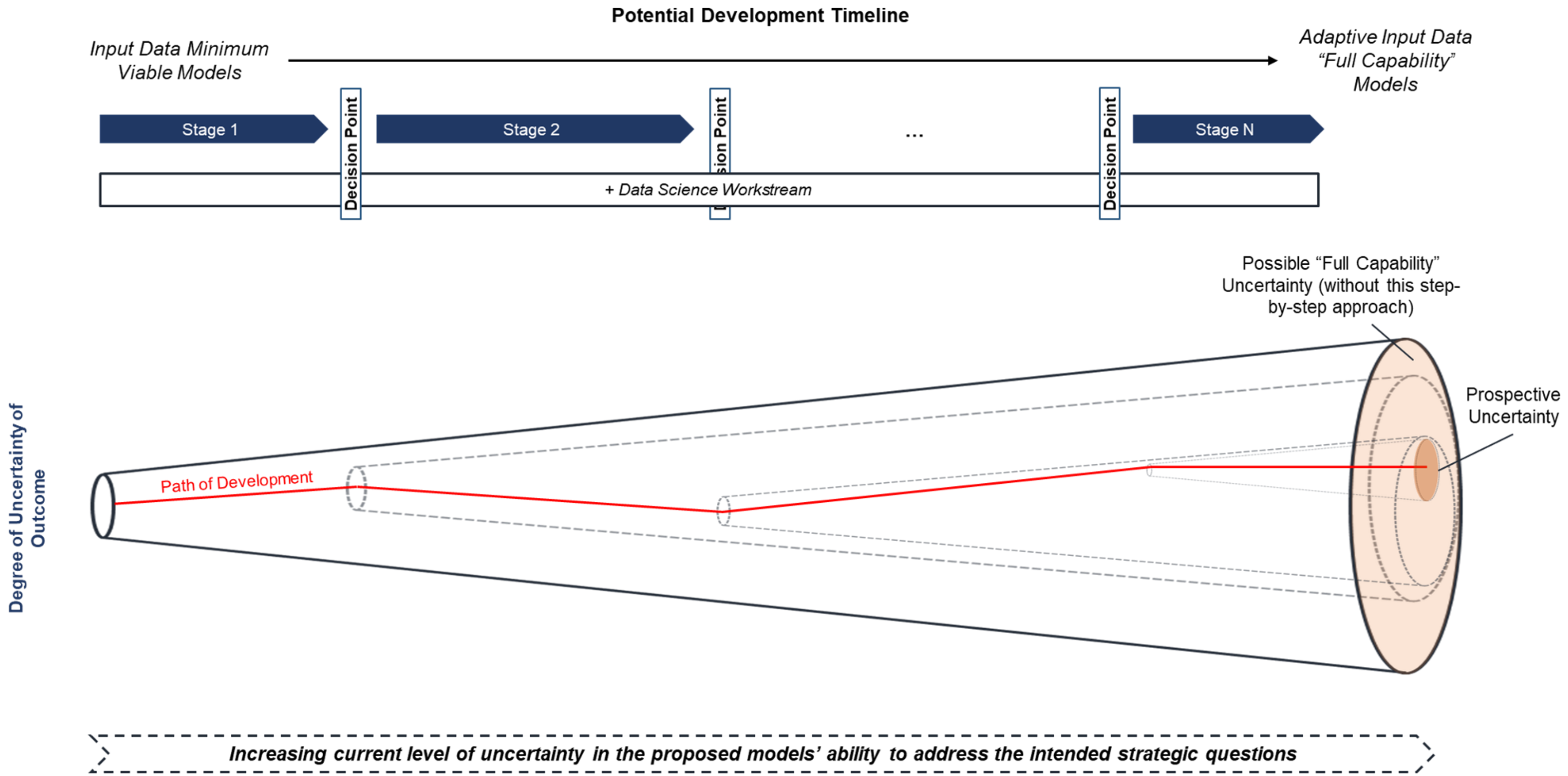


Figure 3: Adaptive Input Data Models Stepwise Approach and "Cone of Uncertainty"

5 Adaptive Input Data Models

This section aims to outline each of the Adaptive Input Data Models considered within the scope of this work. Detailing these individually, they are treated here as separate, siloed components, each with a distinct capability. The way in which these model types could interact and fit together practically can be found within the Architectural deliverables (separate to this report).

5.1 Adaptive Generation Models

5.1.1 Overview

The Adaptive Generation Models described by Google X Tapestry in the output document Advanced Dispatch Optimizer System Roadmap Report are split into two core categories:

1. Thermal generation,
2. Grid scale renewable generation.

[Clarification from Google X suggests that grid scale duration limited assets, such as batteries and pumped storage, are also included within this model group, whilst, for example, smaller instructible batteries connected at the distribution level and participating in the markets are considered as part of the DER Adaptive Input model. These grid scale duration limited assets can generally be modelled in a similar way to the explicitly listed thermal and renewable generator types with regards high-level process and scenario testing capability. Footnotes are used to highlight any specific duration limited asset considerations.]

For each of these categories, the overall model purpose is "*to correct, enhance and create generation input data*" for the optimiser module. This purpose translates into two primary outputs:

- Probabilistic scenario testing capability to forecast the likely response to given dispatch instructions,
- Correction / validation of held static data (e.g., Megawatt (MW) limits, ramp rates).

The core functionality centres around the scenario testing capability, with the improvement of held static data being a useful secondary output. When viewed through a holistic architectural lens, the scenario-based approach provides consistency across the model types and enables coherent testing of output sensitivity to conditions (see Architecture deliverable). Further, whilst it is noted that market participants should generally be providing accurate technical parameters, the correction / validation will catch any discrepancies in performance.

The detail around this specification is given in the "Required Final Capability" section below, with particular focus on the scenario testing capability and associated options.

Note: For context, the decentralised architecture of VirtualES supports the aim for unit level modelling explored in this section. Aggregation to the required spatial level would then be possible to attach to points on the power system model.

The generation model sections below aim to outline some of the current and planned generation forecast capabilities, detail the final vision (highlighting any decision points for consideration), and discuss some comparative gaps. [Note: The main As-Is analysis and gap analysis sit within a different deliverable but relevant data points are discussed here.]

5.1.2 Existing and Planned Capabilities

[See As-Is deliverable for full overview.]

There are currently various existing capabilities relating to the planned generation input data models. Whilst none of these constitute the adaptive-type input model outlined in the end vision documentation, they are important in understanding current processes and associated data. Below is an overview of some relevant elements but, as noted above, the true As-Is analysis sits separately to this report, and as such the below is far from exhaustive.

5.1.2.1 Overview

Forecasted generation values are critical inputs in both the Legacy Dispatch Adviser (LDA) and Modern Dispatch Adviser (MDA). Whilst the full specification of these optimisers is not included here, a brief description is provided below:

The LDA utilises Linear Programming (LP) techniques whilst the MDA uses more advanced Mixed Integer Linear Programming (MILP) techniques to output the dependent variables advised power and advised response. They then compute optimal values for meeting forecast demand and forecast response requirements, subject to constraints.

With specific reference to generation data, the independent variables input into these optimisers include Capped Committed Level (CCL) for conventional units and FX (Forecast power) for windfarms. These input variables are a defined set of expected future values of CCL and FX, calculated as follows:

- CCL = Unit’s declared Physical Notification (PN), as modified by any Bid Offer Acceptances (BOAs); fixed, no modelling required.
- FX = Derived value combining medium-range wind forecasts (from Energy Forecasting System (EFS) / Platform for Energy Forecasting (PEF)) with recent metered values of wind power (by the Wind Metered Power (WiMP) program within BM-SORT) – see detail below.

5.1.2.2 EFS / PEF Generation Capability

The Energy Forecasting System (EFS), gradually being replaced in functionality by the Platform for Energy Forecasting (PEF), covers multiple areas.

At a high level, PEF focuses on four core products (not all relating to generation):

1. National demand forecast,
2. Wind power generation forecast,
3. Solar power (Photovoltaic; PV) generation forecast,
4. Grid supply point (GSP) forecast for demand, solar, and wind.

Machine Learning models are used for the GSP and PV generation products, and a similar model for wind generation is also under construction. Current approaches are generally deterministic (outputting a single, fixed solution per run) and provide a set of forecast variants (minimum, maximum and average). PEF feeds into BM-SPICE, which subsequently feeds into BM-SORT.

5.1.2.3 AMIRA

AMIRA is a third-party tool used by the control room to forecast metered wind generation and the associated error probabilities. None of the outputs feed into any other systems in the control room, with elements being manually typed over by the OEM. Feedback suggests that AMIRA provides a consistently more accurate forecast than PEF.

5.1.2.4 Deep Dive: Wind Forecast Process – Blending

Given the particularly high level of uncertainty observed in wind forecasting, this section provides a more detailed deep dive.

As mentioned, optimiser input windfarm forecasts take the form of an FX (Forecast power) value. This value is calculated by passing wind power forecasts from PEF / EFS via SPICE through a "blending" function within WiMP to incorporate a recent metered value.

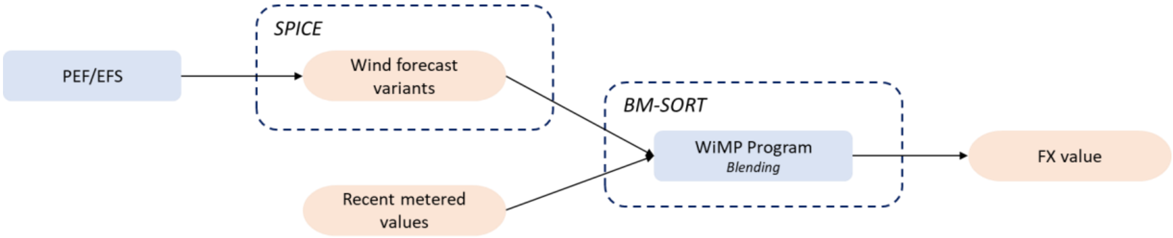


Figure 4: High-level view of wind FX value derivation

The wind forecasts from PEF / EFS are supplied as a set of three variants (expected, minimum, and maximum) into BM-SORT. This gives a more detailed view than a single variant, effectively providing ranges of potential forecasts (low, medium, high) to mitigate the inherent uncertainty in the value.

The "single recent" metered value used within the WiMP program is either power output (MO) or power available (PA). PA is a measure of the power that a windfarm would produce were it not instructed to a lower level by a BOA. As such, when a windfarm is not in a BOA, PA and MO should be approximately equal.

As well as running the "blend" function, the output of the WiMP program also supports manual decision making by control room engineers, giving options to:

- Select which forecast to use (low, medium, high),
- Decide whether or not to use the PA signal.

Methodology Considerations

During discussions held as part of this engagement, there were several concerns raised by ESO SMEs around the accuracy and usability of the above-described method. As indicated, the "blending" process uses only a single recent meter reading. The stochastic nature of wind power means that this may lead to significant forecasting errors. Concerns generally fall into the following categories:

- Blending when in a BOA,
- Trending,
- Gusting.

Blending when in a BOA

One error type specifically arises when a unit without a PA meter is in a BOA. This causes the metered value, and hence the forecast power for the unit as used by dispatch, to be incorrect. A correction that has been proposed (but is yet to be implemented) is instead using the last metered value before the BOA – i.e., taking a value that was independent of the BOA instructions.

Trending

Trending describes a situation in which the "single most recent value" measure (MO or PA) is taken during a notable increasing or decreasing trend in wind speed. As a result, this single value will be highly unrepresentative of the actual wind power over the following hours. Trending is considered to be one of the main sources of error in both MO-blended and PA-blended forecasts.

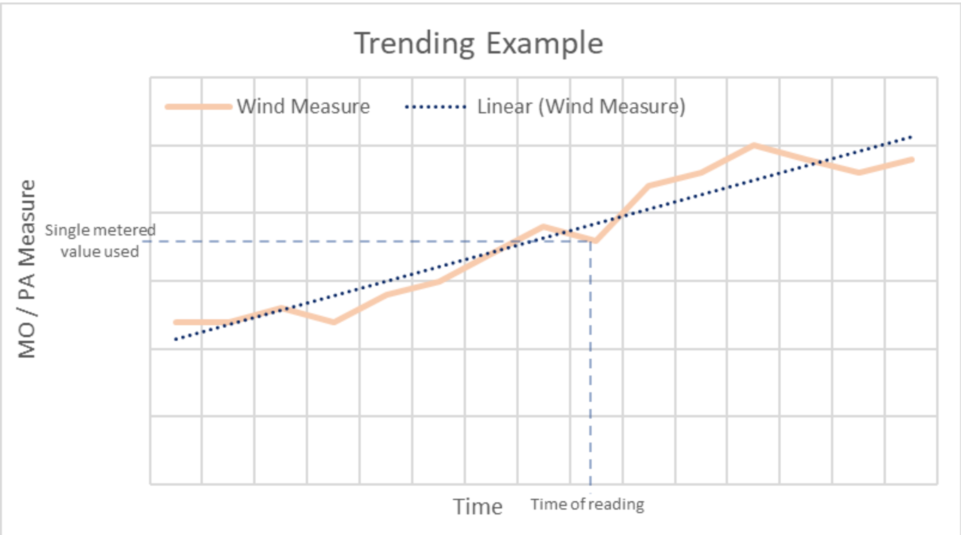


Figure 5: Example of how trending can lead to unrepresentative forecasts

Gusting

Gusting refers to a situation in which the spot value is taken during a wind transient (sudden brief rise or fall). Consequently, said measured value is not representative of the average, leading to errors in forecast. Whilst discussions with control room engineers have indicated that trending is the bigger issue, gusting also contributes to forecasting error.

Figure 6: Example of how gusting can lead to unrepresentative forecasts

With regards gusting and trending, there have been several, relatively simple, possible mathematical solutions proposed by ESO SMEs. These include:

- Rolling average of wind power over past x minutes, for specified x (would deal better with gusting than trending),
- Fitting a rolling straight line to the past x minutes of metered wind power (order 1 polynomial),
- Fitting a rolling quadratic polynomial to the past x minutes of metered wind power (order 2 polynomial, accounting for constant non-zero second derivative),
- Fitting of either a straight line or quadratic polynomial, weighting towards more recent values.

Based upon current understanding, it is recommended that this style of solution be implemented, regardless of future vision and steps towards the final capability.

5.1.3 Required Final Capability

The required final capability discussed below interprets the description provided in Google X Tapestry's Advanced Dispatch Optimizer System Roadmap Report, providing a much greater level of detail, and highlighting arising decision points / considerations.

Each type of generator model (thermal, renewable, and grid scale duration limited assets) aims to provide, for each generator, a half-hourly[10] view of expected actual output (in MW) under a given set of hypothetical dispatch instructions. In other words, the model aims to answer the question:

[10] Half-hourly is the minimum temporal granularity required. Interpolating for shorter steps within the dispatch process would likely provide further beneficial insight.

Given a set of dispatch instructions to test, combined with forecast input data such as weather, likely maintenance etc., what is the predicted actual MW output for a specified generator?[11]

The below figure provides an initial high-level view of the required (supervised) model creation and scenario testing process.

[Note: Whilst the high-level overall process is identical, the differences in consideration between, for example, thermal and renewable generators are discussed below.[12]]

[11] Feedback suggests that a more appropriate question could focus on prediction of unit output before the instruction, as opposed to after (with units generally expected to deliver when instructed, and uncertainty arising from, for example, accuracy of wind unit PNs). Theoretically, this model type could answer both questions given the similar underlying data requirements, with the pre-instruction predicted output tested for relevant timeframes via a "blank" instruction. The need for the additional "dispatch behaviour" element outlined by Google X is therefore open to debate.

[12] For example, a valid point raised is whether or not a Machine Learning model is required for all generators – e.g., a nuclear generator always instructed to provide constant base load with little impact from external factors.

5.1.3.1 Overview

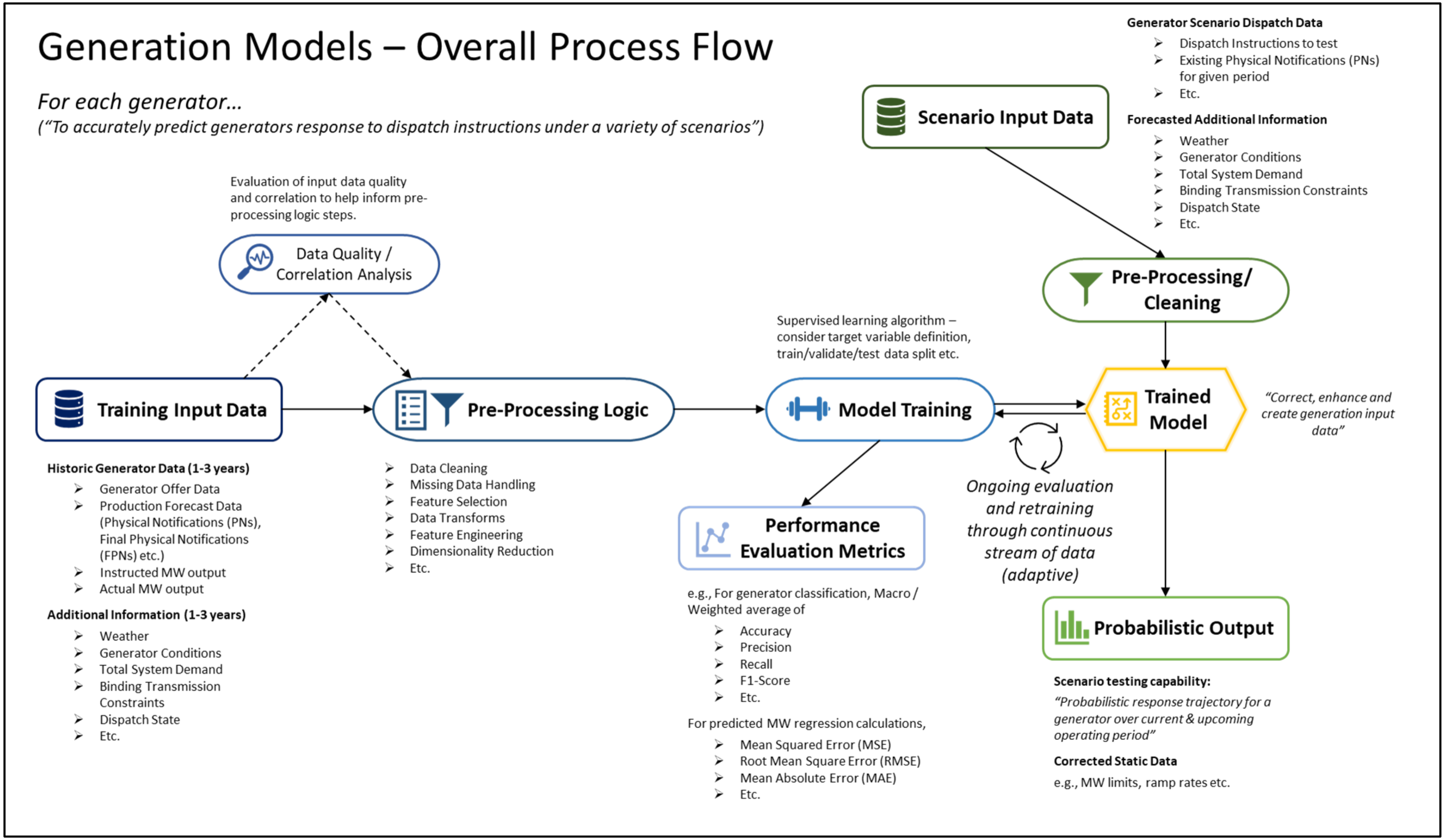


Figure 7: Generation Models – Overall High-Level Process Flow for Training and Scenario Testing

[Note: Feedback suggests that this outlined process is similar in principle to the PEF Machine Learning models, though their blended output is deterministic.]

Briefly describing these stages:

Training Input Data

The set of historical (labelled) data that is used to train the Machine Learning model in question. Utilising this data, the model learns how the different variables relate to the intended target being predicted, in this case the actual MW output (see section "Data Requirements Overview" for more detail).

Data Quality / Correlation Analysis

This crucial first step evaluates the quality, format, and inter-relationships of variables in the available training data. The outcomes of the analysis help inform the usability of the data as well as dictate necessary Pre-Processing steps.

Pre-Processing Logic

Logic implemented here cleans and transforms data such that it can be used in the chosen model. As indicated, steps may include, but are not limited to:

- Data Cleaning
- Missing Data Handling
- Feature Selection
- Data Transforms
- Feature Engineering
- Dimensionality Reduction

Model Training

The model in question uses supervised learning techniques to predict the actual half-hourly MW output for a generator under given dispatch instructions. Training on the processed data will output the trained model for scenario testing use.
[Note: This model could use a Regression or Classification algorithm (though more likely Regression) – see discussion below.]

Ongoing Evaluation and Retraining through Continuous Stream of Data (Adaptive)

The purpose of Adaptive Machine Learning models (as opposed to Traditional Machine Learning) is to react to changing data sets, utilising real-time data to "adapt" and more accurately represent real-world situations. As such, there is an element of continuous improvement.

Performance Evaluation Metrics

Such metrics are particularly important in supporting the ongoing evaluation and retraining element at the heart of adaptive modelling. Difficulties in, for example, defining the correct target metric mean that evaluation metrics contribute to problem structure and definition in addition to hyperparameters etc.

Depending on whether a Regression or Classification algorithm is chosen for this problem, there are different evaluation metrics which will be critical in assessing the quality of the model and tuning of hyperparameters during the training stage. Example metric types include:

Classification

- Accuracy
- Precision
- Recall
- F1-Score

Regression

- Mean Squared Error (MSE)
- Root Mean Square Error (RMSE)
- Mean Absolute Error (MAE)

<u>Scenario Input Data</u>

The set of input data to run the trained model on. This includes both forecasted dependent variables as well as the specific dispatch instructions to test (see section "Data Requirements Overview" for more detail).

<u>Probabilistic Output</u>

The output of the model's scenario testing capability. Considerations around the form of the model output, as well as the final output from potentially running multiple scenario tests to account for uncertainty in the forecasted input variables, are discussed at length in sections "Modelling Approach Considerations" and "Scenario Testing Capability and Output". These sections explore the possibilities of probabilistic base models (as opposed to point estimates) and probabilistic outputs from scenario testing[13].

5.1.3.2 Data Requirements Overview

Within the process flow shown, data requirements can broadly be split into two categories: Historic Training Data and Scenario Input Data. Potential data sources are discussed in the data availability section.

For completeness in a single view, data variables listed below under Historic Training Data and Scenario Input Data cover the requirements for all generator types. In practice, certain variables are more relevant for particular generator types than others. For example, weather data is primarily associated with renewable generators and will likely have a comparatively insignificant impact on thermal generator output[14].

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[13] As noted previously, when viewed through a holistic architectural lens, the scenario-based approach provides consistency across the model types and enables coherent testing of output sensitivity to conditions (see Architecture deliverable).
[14] Note: there is evidence that temperature affects the ramp up rates of thermal generators.

Historic Training Data

Training data refers to the set of historical (labelled) data that will be used to train the first iteration of the model. Said training data will later be updated over time in line with a defined re-training schedule.

The training data for these models consists of, for each generator in question, Historical Generator Data (i.e., *What has happened previously with regards expected vs. actual generator outputs within the Balancing process?*) and Additional Information for correlation tests (i.e., *What external factors may account for any discrepancy observed in expected vs. actual output?*).

Table 3: Generation Models – Training Data

Category	Data	Description	Frequency	Total Time
Historical Generator Data	Generator Offer Data	Generator BOAs, Bid Offer Data (BOD), including increase / decrease limits and associated prices.	Half-hourly (for each dispatch interval)	At least 1 year (Tapestry minimum), preferably approx. 3 years (IBM view).
	Production Forecast Data[15]	Generator forecast output figures over time (including PNs, Final Physical Notifications (FPNs)).	Half-hourly (for each dispatch interval)	
	Instructed MW output	Instructed MW output by generator over time.	Half-hourly (for each dispatch interval)	
	Actual MW output	Actual MW output by generator over time.	Half-hourly (for each dispatch interval)	
Additional Information	Weather	Weather data for each generator location (temperature, precipitation, UV levels, wind speed etc.).	Half-hourly profiles	
	Generator Conditions	Generator conditions over time, including maintenance activities (both planned and unexpected outages).	Ad-hoc	
	Total System Demand	Total system demand over time.	Half-hourly	
	Binding Transmission Constraints	All active constraints over time (both planned and unexpected).	Ad-hoc	
	Dispatch State	Dispatch state by generator over time (e.g., ramping up,	Ad-hoc	

[15] In the case of grid scale batteries and pumped storage, this input is assumed to include associated "state of charge" data.

		holding etc.) – to understand, for example, ramp-up rates.		

As hinted at in the above table, the total historic timeframe that constitutes "sufficient" data for training is, at this stage, indeterminate. Tapestry correctly notes that there is a balance to be struck between model accuracy and data gathering complexity. As such, it is important to remember that further re-training will be continuous as more data is collected, thus improving the accuracy of the model.

Scenario Input Data

Scenario Input Data here refers to the set of information fed into the trained model to produce the probabilistic output desired. What the model requires as input is a set of forecasted data covering all the previously defined "Additional Information" variables (forecasted for the given timeframe in question), as well as the particular dispatch scenario to be tested.

In other words, for the given future time in question, the model input data consists of, for each generator, Scenario Dispatch Data (i.e., *What set of dispatch lever options are we looking to understand the impact of?*) and Forecasted Additional Information (i.e., *How do we expect the factors affecting dispatch response to be behaving over the time in question?*).

Table 4: Generation Models – Scenario Input Data

Category	Data	Description	Time
Scenario Dispatch Data	Theoretical Dispatch Instructions	Set of potential dispatch instructions to be tested in the model.	Given future time period in question.
	Existing PNs for given period[16]	Existing generator PNs for the time period being considered.	
	Generator Offer Data	Available Generator Bid Offer Data (BOD), including increase / decrease limits and associated prices. (Relevance dependent on when the model is being run relative to the period in question.)	
Forecasted Additional Information	Weather	Weather data for each generator location (temperature, precipitation, UV levels, wind speed).	
	Generator Conditions	Generator conditions over time, including maintenance activities (both planned and unexpected outages).	
	Total System Demand	Total system demand over time.	

[16] Again, for grid scale batteries and pumped storage, this input is assumed to include associated "state of charge" data.

	Binding Transmission Constraints	All active constraints.	
	Dispatch State	Dispatch state changes by generator over time (e.g., ramping up, holding etc.).	

[Note: Given the number of variables, the scenario definition process itself could exist as a separate problem. Management of this is briefly discussed in the below section "Scenario Testing Capability and Output", as well as within the Architecture deliverable.]

5.1.3.3 Data Models

Further, the below logical entity-relationship diagrams provide a view of how both the scenario input data sources, and separately the training data sources, could relate and be structured.[17]

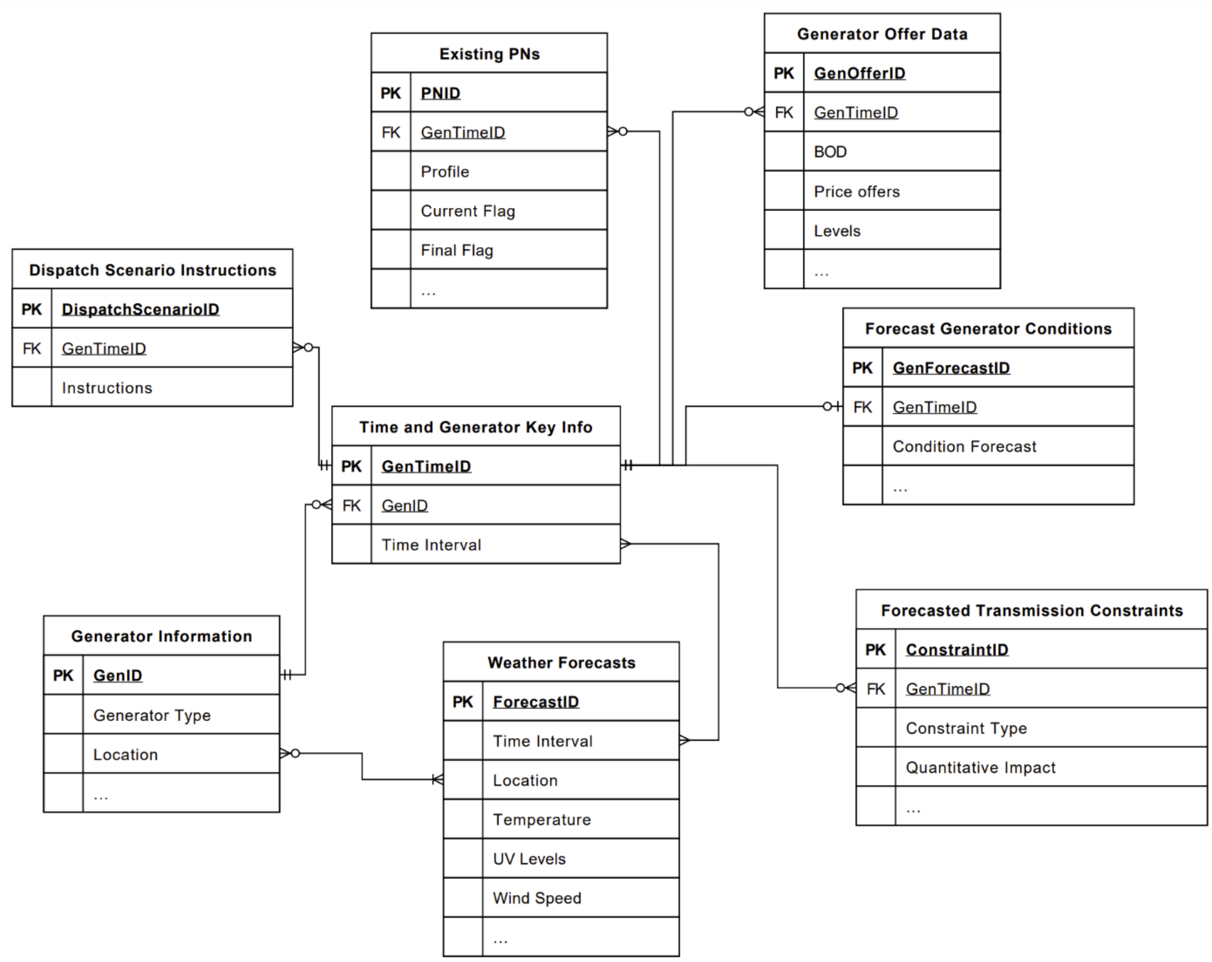

Figure 8: Generation Models – Example view of data model for scenario input data sources

This model exemplifies the relationships between the different data sources and provides a practical view as to one way the end vision data structures could be realised. In this sample

[17] See section 7 for overview of entity-relationship notation.

structure, the hypothetical dispatch instructions to be fed into the scenario testing capability can be linked via different keys to the other model input data.

As an example, the dispatch scenario instructions to test within the generation models are linked via a key to the specific generator ID and time interval being trialled. Shown by the connection types in the above diagram, each set of instructions will join to precisely one Generator / Time Interval combination key, whilst each such key may link to multiple trial instructions. The generator ID can then be further used to gather information such as location (at required level of granularity) to link weather forecasts etc.

Similarly for the listed historic training data:

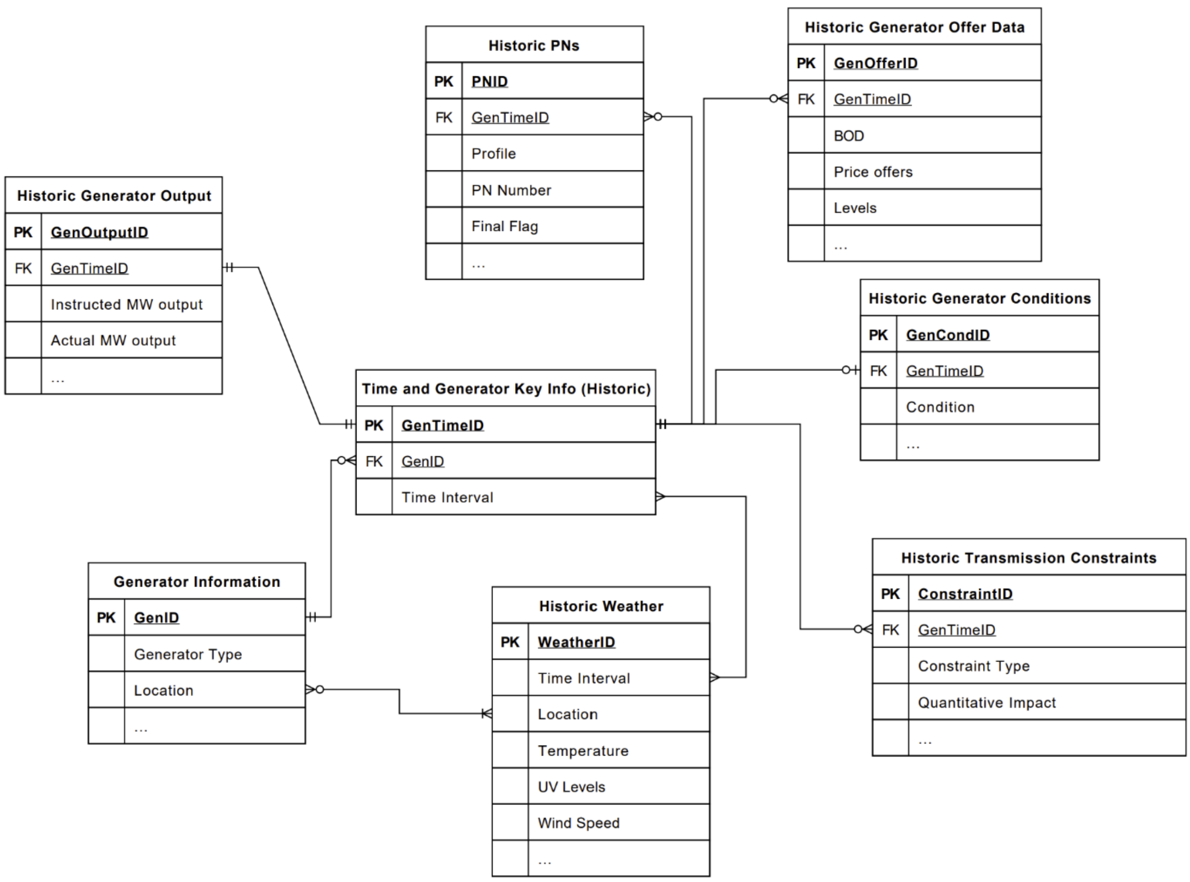

Figure 9: Generation Models – Example view of data model for training data sources

Overall, a schema of this type would integrate seamlessly with the final vision model, assuming any technical constraints are not limiting.

5.1.3.4 Modelling Approach Considerations

A major decision point in writing a full specification for these sets of models would be defining the modelling approach. The “correct” modelling technique is dependent on the input data, desired output format, and intended model usage.

In selecting a modelling methodology for this supervised learning problem, two core questions arising are:

- Should this be treated as a regression or classification problem?[18]
- Is the desired model output deterministic or probabilistic?[19]
  [Note: The model output type for a single iteration does not necessarily equal the final output type for the given use case following multiple scenario tests (see Scenario Testing Capability and Output).]

<u>Regression vs. Classification Definitions</u>

Regression and Classification are both types of Machine Learning problem, crucially differing in high-level approach and output.

A regression model aims to predict a continuous value by understanding the underlying relationships between this continuous target variable and numerical input data. Common regression algorithms include Simple Linear Regression, Multiple Linear Regression, and Polynomial Regression.

Classification models instead predict assignment to a set of discrete (discontinuous) output groups by mapping across from input variables (not necessarily numeric). Common classification algorithms include Decision Tree Classification, Random Forest Classification, and K-Nearest Neighbour.

<u>Deterministic vs. Probabilistic Definitions</u>

A "deterministic" model would produce for example, for each generator, a "single value" predicted actual output for each half-hour interval given a set of input conditions. This model would always produce the same output for a specified set of inputs. [Note: This "single value" could take the form of a number (regression) or group (classification).]

In contrast to a "single value" output deterministic model, a "probabilistic" model incorporates randomness to produce a distribution of outputs. As a result, one is able to incorporate confidence intervals into decision-making.

<u>Considerations for Generation Input Data Models</u>

As referenced above, this decision around modelling methodology depends on the form of input data, the desired output format, as well as more generally the planned business use of the model.

[18] This is informed in part by whether or not the related time-series data is numerical / continuous.
[19] Depends on the underlying level of forecast uncertainty and intended usage.

Deterministic Regression	**Deterministic Classification**
Predicting a single numerical value for actual output for each half-hour interval, given a set of input conditions.	*Predicting a single class (group) value for actual output for each half-hour interval, given a set of input conditions.*
Probabilistic Regression	**Probabilistic Classification**
Giving a probability distribution across numerical values for actual output for each half-hour interval, given a set of input conditions.	*Giving a probability distribution across class (group) values for actual output for each half-hour interval, given a set of input conditions.*

Figure 10: Generation Models – Matrix of modelling techniques

This distinction between methods is relatively high-level and generic to give a broad overview of the differences and considerations that feed into a decision. The practical differences between these methods are widely documented and hence only discussed briefly here.

Some of the factors to consider are highlighted below.

Algorithm Type	Pros	Cons
Regression	• Clearly understood and interpretable numerical prediction for actual output for each half-hour interval.	• Potential need for one-hot-encoding or other data transformations for numerical input.
Classification	• Choice of either numerical buckets or categorical output. • Freedom of definition of categorisation.	• Not as relevant and interpretable for numerical predictions. • Less clear as to how output will inform optimisation.

Model Type	Pros	Cons
Deterministic	• Simplicity and understandability of single value output.	• May not provide the breadth of insight required.
Probabilistic	• Detailed output, providing a more holistic view of the problem by giving an idea of confidence intervals, etc. – particularly useful for problems with a high	• May require more manipulation of output to integrate with optimisation modules (dependent on optimiser design).

	degree of underlying uncertainty.	

Whilst there is no "correct" answer in considering these options, and all factors should be considered carefully when deciding, the ***desired output most likely points towards a regression-style problem.***

5.1.3.5 Scenario Testing Capability and Output

Depending on the choice of modelling approach (see above) and the desired final output format, there are several different process-run options to consider.

<u>Deterministic Model, Running a Single Scenario to Output the Single "Most Likely" Response</u>

By far the simplest option involves running a single scenario through a deterministic model, thus outputting a "single value" response that can be fed into the optimiser modules as required. The forecasted input data for the time period in question would represent the "most likely" scenario.

<u>Deterministic Model, Running Scenario Testing over the Input Data Parameter Space</u>

A probabilistic-style output could be produced from a deterministic model by running a multitude of different scenarios through the model to gain an idea of sensitivity to forecasted input conditions. This would likely be achieved by running scenarios over a defined input data parameter space.

For example, such a parameter space for the forecasted variables at a generator location (for a given time period) could be constructed with either discrete values or probability distributions as:

Table 5: Generation Models – Example parameter space for scenario testing

Category	Data Type	Parameter	e.g., Discrete Range	e.g., Distribution
Forecasted Additional Information	Weather	Temperature (°C)	[16, 17, ...]	$T \sim \mathrm{N}(18,4)$
		Wind speed (mph)	[10, 12, ...]	$v \sim \Gamma(15,1)$
		UV Index	[3, 4, ...]	$\vartheta \sim \Gamma(7.5,1)$
		Etc.		
	Generator Conditions	Active Maintenance Boolean	[0, 1]	$\kappa \sim Ber(0.1)$
		Etc.		
	Total System Demand	Total demand for given area (MW)	[500, 550, ...]	$\Delta \sim \mathrm{N}(650,70)$

	Etc.			

[Note: example discrete ranges and distributions are purely illustrative.]

Depending on the size of the parameter space and computational capacity / runtime limitations, one could either run a scenario for every combination of parameter values (if using discrete value options) or a fixed number of scenarios representing a random sample of possibilities. Use of probability distributions rather than discrete value ranges will likely improve the overall accuracy of the combined scenario output.

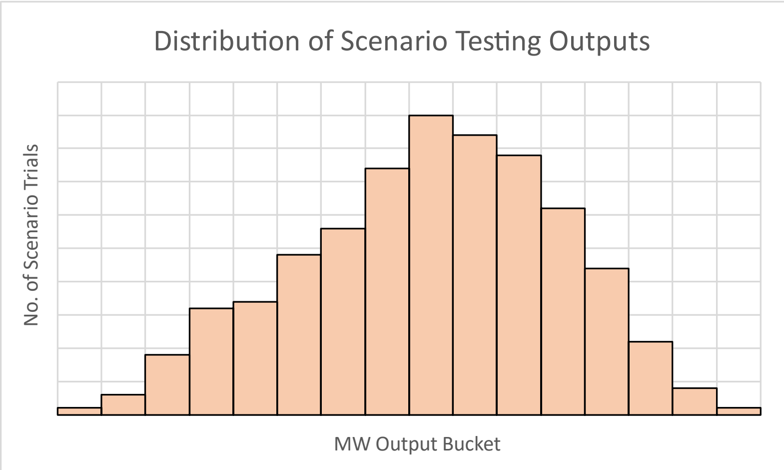

Figure 11: Generation Models – Example distribution output from running multiple trials with a deterministic model

<u>Probabilistic Model, Running a Single Scenario to Output the Single "Most Likely" Response Distribution</u>

Similar to running a single scenario with a deterministic model, a probabilistic model here would provide a single probability distribution output. Again, the forecasted input data for the time period in question would represent the "most likely" scenario.

<u>Probabilistic Model, Running Scenario Testing over the Input Data Parameter Space</u>

Arguably the most complex option involves running multiple different scenarios through a probabilistic model to obtain a set of probability distributions. As before, this would likely be achieved by running scenarios over a defined input data parameter space, with individual variable parameter spaces constructed either discretely or using distributions.

This output set of probability distributions would provide the most comprehensive view of sensitivity to forecasted input conditions, and variability in likely generator response. The usefulness of such an output is dependent on intended model usage in isolation (outside the optimiser context) and required input format for the optimiser module.

As indicated above, the choice between deterministic and probabilistic modelling depends on multiple factors and each has associated pros and cons. With regards the "single scenario" vs. "multi-scenario" run process choice detailed above, the core considerations are:

- What is the required input for the optimisation module(s)?
  [This is dependent on the optimiser architectural design.]
- Will these Generation Adaptive Input Models be used in isolation to gain insight? If so, a more holistic multi-run process capability may be useful.

5.1.3.6 Further Considerations

Further considerations around the above described "Final Capability" are recorded below.

Utilising New Units without Sufficient Historic Training Data

One may question how to "correctly" incorporate new units given they will not have sufficient levels of historic training data, as defined above.

The nature of adaptive models is that they undergo a cycle of continuous improvement via a stream of real-time data. In other words, they continually improve over time as more data becomes available. Subsequently, the question becomes "*How can we utilise existing information to create a proxy for new units during the initial stages of model development where little training data is available?*". And further, "*At what threshold is the continuously improving model deemed fit for use?*".

Comparison exercises could enable initial use of trained models for "similar" units when a new unit enters the balancing mechanism. Alternatively, new units could be simply treated at face value (exact response to any reasonable dispatch instructions) whilst model development is underway.

Differences between Thermal and Renewable Generators

The way in which thermal and renewable generators participate in the market is significantly different, resulting in different underlying issues. Consequently, the associated value of the above modelling approach varies by use case. Feedback suggests that this modelling capability is far more valuable for renewable units than for thermal – with thermal units generally expected to deliver when instructed, and poor accuracy of, e.g., wind PNs creating notable uncertainty. The forecasting applied to generator types can readily be split into modelling of uncertain resources (e.g., wind, solar) and overall balancing process performance.

Considerations stemming from this include prioritisation of generator model development and differentiation between evaluation measures.

5.1.4 Data Gap Analysis

As is to be expected when defining a new, innovative capability, none of the existing or planned processes completely meet the requirements outlined in "Required Final Capability". However, mapping said requirements to existing data sources and techniques provides a clearer view of missing elements, as well as next steps.

As noted previously, the true gap analysis deliverable sits separately to this report, and the below section therefore comments only on data availability and quality.

5.1.4.1 Overview

There are many Generation-related forecasts and optimisation elements currently in use. Where the novelty of the final vision Generation Input Data Model lies is in the appreciation of the potential discrepancy between FPNs altered by BOAs and actual recorded output. Accurate prediction of this potential discrepancy for each generator at a given time should lead to improved decision making around the dispatch process.

The section “Existing and Planned Capabilities” above references defined sets of optimiser input data which represent expected future values of generation in the form of CCL and FX. Whilst these values would be important inputs into the final vision model, there is at present no dispatch scenario testing process as detailed in “Required Final Capability”.

5.1.4.2 Availability of Data

The below tables provide an overview of the currently understood data availability gap.

Historic Training Data

There is a hope that some of this historic data may exist in yet unexplored data silos. However, the working theory from SMEs interviewed as part of this project is that ***approx. 3 years of data collection in real time would be required in order to meet the historic "Additional Information" data requirements outlined[20].***

Table 6: Generation Models – Training Data Availability

Category	Data	Frequency Required	Total Time	Currently Understood Availability
Historical Generator Data	Generator Offer Data	Half-hourly (for each dispatch interval)	At least 1 year (Tapestry minimum), preferably approx. 3 years (IBM view).	Available, stored in National Grid Economic Database, NED (from the start of New Electricity Trading Arrangements (NETA) in 2001).
	Production Forecast Data	Half-hourly (for each dispatch interval)		Available, stored in NED (from the start of NETA in 2001).
	Instructed MW output	Half-hourly (for each dispatch interval)		Available, stored in NED (from the start of NETA in 2001).

[20] It is worth noting that the full data requirements listed may not be necessary for a first model iteration. Analysis of model performance over time will indicate whether the currently unavailable variables will significantly improve forecast accuracy.

	Actual MW output	Half-hourly (for each dispatch interval)		Available, stored in Data Historian.
Additional Information	Weather	Half-hourly profiles		Some wind related data available (wind speed vs. wind power), stored in NED – unsure of exact storage length. Alternatively available through MET Office Weather Data for Business (wind, temperature, radiation levels etc.).
	Generator Conditions	Ad-hoc		Not aware of existence. *Perhaps generators hold this historic data?*
	Total System Demand	Half-hourly		Demand profiles kept for selected days (e.g., Coronations). Not aware of more extensive records.
	Binding Transmission Constraints	Ad-hoc		Not aware of any archiving of constraints.
	Dispatch State	Ad-hoc		Unclear – can perhaps be deduced but may not be required.

Scenario Input Data

Availability of the Scenario Input Data "Additional" variables is inherently related to the above availability of Training Data. The difference arises in the time horizon being considered, with Training Data being historical and Scenario Input Data being forward-looking.

Data groups required for scenario testing are generally more available, and hence not as restrictive to model development as the above training data.

Table 7: Generation Models – Input Data Availability

Category	Data	Time	Currently Understood Availability
Scenario Dispatch Data	Theoretical Dispatch Instructions	Given future time period in question.	To be created as part of model input.
	Existing PNs for given period		Received by ESO and available. [Quantity dependent on time horizon of future time period in question.]
	Generator Offer Data		Received by ESO and available. [Quantity dependent on time horizon of future time period in question.]

Forecasted Additional Information	Weather		Forecast data available and utilised.
	Generator Conditions		Dependent on time horizons – not aware of longer-term planning from all individual generators.
	Total System Demand		Forecast data available and utilised.
	Binding Transmission Constraints		Forecast data available and utilised. [When considering short time horizons, active transmission constraints can be obtained from the Adaptive Transmission Model.]
	Dispatch State		Current dispatch states, requirement for "warming" etc. understood.

5.1.4.3 Data Quality / Granularity Analysis

The quality and granularity of data is of great importance when building a model of this type. Due to security measures regarding Critical National Infrastructure (CNI) designation, data has not been able to be extracted for IBM-run data quality analysis. Instead, comments below reflect the current understanding of relevant data quality and granularity.

<u>Data Historian</u>

The Data Historian system is highlighted above as the location of historic actual MW output data for each generator. Whilst this data does indeed exist, ESO SMEs have noted several points for consideration regarding quality, granularity, and extraction.
[Note: There is no complete data dictionary held for Data Historian.]

- *Data timestamps are inconsistent and muddled.*
  This is due to the collection mechanism in which data is only updated when there is a change in value. As a result, there is no consistency in timestamps across units. For example, some meter values are captured at a frequency of up to five times per second, but if the generator is switched off then no data is recorded until the next non-zero reading. One could consider normalising timestamps by using average values across, for example, one second timeframes, but this may be insufficient when examining faults and outage scenarios with very fast timescales.
- *No differentiation is made between out-of-service and permanently decommissioned units.*
  As a result of the data collection mechanism described above, there is no distinction in the data between units that have been permanently decommissioned and those that are temporarily out-of-service / turned off. In both cases, we simply observe a period of no data, thus leading to potential confusion.
- *Some units have incorrect flow direction data (positive vs. negative values) due to issues with physical asset wiring.*

Data quality issues such as these are relatively obvious when manually viewed (with values trending in the wrong direction), but it is preferable to fix these at the asset rather than implementing ad-hoc data transformations which may later need to be reversed.

- *Static generator data is generally seen as untrustworthy.*
  Static generator information variables such as latitude / longitude were often entered manually and, consequently, are not considered to be accurate. For example, multiple wind generators in relatively close proximity are given the same location data for simplicity, ignoring the nuanced differences.
- *Data extraction is very slow.*
  Retrieval of data was not the primary purpose when Data Historian was initially implemented. As a result, it is very slow and difficult to bulk pull data via the associated Application Programming Interface (API).
- *Future software changes may result in Data Historian being sunset in favour of a new system (requiring data migration, re-structuring etc.).*
  Planned SCADA upgrades and software renewals will likely result in Data Historian (which is fed from SCADA) being removed from service and replaced within a few years.

<u>National Grid Economic Database (NED)</u>

There is no known complete data dictionary held for NED, and tables have varying levels of meta data detail. Consequently, knowledge differs greatly by table / use case, with lots of views never used.

<u>Weather Data – Anecdotal</u>

Information from ESO SMEs suggests that some historic wind data is stored at one minute resolution, averaged from around four spot values. From a temporal perspective, this enables very fine-grain correlation analysis. Whilst one minute frequency may not be used in the final models, this gives the flexibility to aggregate to a suitable level.

<u>Weather Data – PEF</u>

The PEF data dictionary, whilst high-level, describes several different weather datasets that are downloaded and manipulated (calculating national averages etc.) via defined data pipelines:

- Weather Actual,
- Weather Forecast,
- Weather Reference Data.

The static weather reference data is used in PEF to align site IDs to physical locations (latitude, longitude, altitude) and their associated characteristics.

As for the actual and forecast datasets, the below table provides a high-level summary.

Table 8: PEF Weather Data

Dataset	Resolution	Update Frequency	Latency	Horizon	Timestamp	Source System	Assumptions
Weather Actual	Hourly	Hourly	Scheduled job, 20 minutes after MetOffice release.	14D	Weather actual in recent history – different for each variable.	MetOffice	- Data is loaded in time order with no gaps.
Weather Forecast	Hourly	2 Hourly	Scheduled job, 20 minutes after MetOffice release.	14D	Weather forecast for each point in time.	MetOffice	- Latest forecast received is the best for the dates covered. - Data is loaded in time order with no gaps.

Whilst the documentation does not provide an explicit list of ingested variables, fields used within the calculation steps include, for each site:

- Radiation
- Temperature
- Precipitation
- Relative Humidity
- Air Pressure
- Dew Point Temperature
- Visibility
- Wind Speed
- Wind Gusts

Any calculated national averages utilise a fixed national weighting applied to the seven stations from which data is received:

Table 9: PEF Weather Data – Site Weightings

Station Name	Code	Weight
Glasgow	GLAS	0.10
Leeming	LEEM	0.07
Harwarden	HAWA	0.14
Leconfield	LECO	0.07
Birmingham	BIRM	0.16
Bristol	BRIS	0.18
Heathrow	HEAT	0.28

5.1.5 Regulatory Considerations, Explainable AI, and Process Impacts

There are multiple "Explainable AI" related areas for consideration within the generation space.

5.1.5.1 Dispatch Instructions

Given as an example earlier, introduction of AI-generated dispatch instructions creates a requirement around the ability for humans to understand, analyse, and improve the underlying logic. Whilst this applies to all of the Input Data model areas feeding into the optimiser, specific generation questions may include:

- In situations where the lowest price units are not utilised, what are the underlying reasons? Is there, for example, a historically noted issue with said units that may result in sub-par performance against expectation? Do forecasted external factors favour other units with regards expected response? Or do the core logical reasons sit within other areas (e.g., transmission constraints, movement of interconnector markets etc.)?

5.1.5.2 Transparency with BMUs and Contractual Relationships

Another consideration around AI transparency questions to what degree ESO should be responsible for informing and educating market participants on the unit-level input metrics and optimiser processes that would determine their usage.

This may not be required under current contractual relationships. However, in the event of edge cases whereby a generator has been perceived to be "unfairly" treated, a level of transparency may be required.

5.1.5.3 BMU Obligations

As noted by an ESO Operational Manager in the document *Virtual Energy System - Advanced Dispatch Optimiser Google X Comparison (April 2022)*, the very nature of the proposed Generation Adaptive Input Models raises questions around the wider market obligations. The proposal detailed above aims to correct generator input data and use past behaviour to predict output response. They observe that "*this raises wider questions on generators' obligations to provide accurate data, follow instructions and the market incentives around them*". These arising concerns are important considerations in defining the new AI-led landscape.

5.1.6 Discussion Point: Is this style of modelling the best approach to address the core issue?

As mentioned above, the stark differences between the balancing processes for thermal and renewable generators leads to a clear distinction in issues faced (see Further Considerations discussion). Due to both the nature of regulation and associated forecasting challenges, renewable generators' PNs contribute significantly more to the overall uncertainty level.

This raises the valid question:

Should ESO be focusing on modelling this renewable error (as outlined in this capability), or instead making regulatory changes to greatly reduce the error?

Thermal generators participate in the market under a strict set of rules regarding financial incentives etc., thus promoting more accurate PNs and greater reliability. Aligning the renewable regulation rules to this structure used for thermal generation (or similar) could, theoretically, improve the reliability of renewable PNs.

However, the differences in regulation were, in part, designed to encourage more renewable market participants as the UK consciously moves towards its Net Zero target. In altering these regulation rules, ESO potentially risks alienating existing renewable units and decreasing the rate at which new units enter the market.

Therefore, perhaps a more realistic approach (balancing improvement of PN quality and the encouragement of new renewable units) would be a hybrid option. This could take the form of different regulatory rules depending on unit capacity. For example, larger renewable generators could be bound by stricter financial incentives to force improved PN accuracy, whilst smaller units could run under the current agreement.

[Note: Discussions with the regulator are included as part of the roadmap deliverable.]

5.1.7 Next Steps

The separately delivered "Roadmap" output will specify next steps in working towards the more holistic longer-term end vision.

However, as indicated above, there are a few immediate steps that can be taken to improve current capability and progress this area. These include:

1. Implementation of simple rolling window / polynomial fit mathematical solutions to wind values to mitigate the impact of gusting and / or trending.
2. Altering the use of wind generator metered values to instead use the last metered value before the BOA.
3. Addressing of data availability issues by planning for a multi-year data collection period where necessary for model training purposes.
4. Discussion with regulators regarding possible actions to improve PN accuracy.
5. Initial Data Science workstream activities (see 4.2.1).

Actions 1. and 2. are suggested quick improvements arising from conversations with ESO generation SMEs. Whilst these are considered by SMEs to be appropriate actions, further analysis post-trial implementation would be required to quantitively validate the expected improvement in forecasting capability.

5.2 Adaptive Transmission Model

5.2.1 Overview

At a high-level, the Adaptive Transmission Model referred to by Google X Tapestry in the output document Advanced Dispatch Optimizer System Roadmap Report aims to:

- Provide a view of prioritised active transmission constraints to be fed into the optimiser module,
- Suggest a form of suitable "control strategy" to mitigate resulting effects.

Overall, this approach sees benefit coming from improved speed and efficiency of dispatch optimisation engines as well as enhanced situational awareness for transmission operators.

The difficulty arising with this model group in particular, due to its complex nature, is the lack of specified detail around structure and potential implementation in Tapestry's report. Consequently, it is hard to form a detailed vision of what was intended. To address this, two distinct final visions are outlined below:

1. A high-level interpretation of Google X's report,
2. A far more detailed "IBM View" of constraint modelling, including analysis of the individual constraint problem types.

The detail around these specifications is given in the "Required Final Capability" sections below, with distinction, as mentioned, between the high-level interpretation of the Google X Tapestry report and a formed IBM-view.

The transmission model sections below aim to outline some of the current and planned constraint understanding capabilities, detail both the high-level Tapestry report interpretation and IBM view final visions (highlighting any decision points for consideration), and discuss some comparative gaps. [Note: The main As-Is analysis and gap analysis sit within a different deliverable but relevant data points are discussed here.]

5.2.2 Existing and Planned Capabilities

[See As-Is deliverable for full overview.]

Below is an overview of some relevant elements but, as noted above, the true As-Is analysis sits separately to this report, and as such the below is far from exhaustive.

The explored existing / planned transmission capabilities can be readily broken down by system into:

- Power Network Analysis (PNA),
- Online Stability Analysis (OSA),
- Offline Transmission Analysis (OLTA),
- Network Control Management System (NCMS).

5.2.2.1 Power Network Analysis (PNA)

PNA runs offline static single point contingency analysis every 10 minutes to secure the network as per the Security and Quality of Supply Standard (SQSS) licence obligations, ensuring that no constraints (thermal, voltage, fault level, generator stability) are violated.

It does this by running thousands of "what if" scenarios through an underlying base network model of the GB power system (fed manually from OLTA) to continuously monitor system health – at each stage determining if the network is still operating within licence obligations. These "what if" scenarios may include "*What would happen if this particular generation asset were to trip?*" or "*What would happen if these two generation assets tripped at the same time?*".

Generally speaking, there are two forms of contingency scenario: "Database defined" contingency (determined completely by licence obligations), and "User defined" contingency (scenarios that control room users identify as useful and are thus created "on the fly"). This capability allows control room engineers to run offline analysis to identify any weaknesses in the current state of the system.

Whilst this repeated single state contingency analysis is arguably the most relevant functionality of PNA, it is also worth noting the fault level analysis module. In essence, this is short circuit analysis – studying exposure and tolerance of assets to different faults. If a circuit breaker or other piece of network equipment is deemed to be unable to tolerate a tested fault, this could be a major issue (i.e., this module represents more than just a safety-type analysis).

5.2.2.2 Online Stability Analysis (OSA)

OSA is a real-time tool that performs stability constraint security assessments and provides this information to control room users. It does this by taking multiple inputs, including:

- Load flow (state estimation from PNA),
- Real-time status of intertrip modes, telemetry on integrated Energy Management System (iEMS) etc.,
- Dynamic time-based models, such as generator dynamic models, PSS (Power System Stabilisers), wind farm models, reactor models etc.,
- Criteria data (can be thought of as limits),
- Manually defined contingencies (different to PNA contingencies).

The dynamic models are manually converted from OLTA. This process is significantly more complex than the transfer of the load flow base model from PNA, and as such is only carried out on a 1-2 week frequency.

5.2.2.3 Offline Transmission Analysis (OLTA)

At a high level, OLTA is an offline network study model (i.e., it is not fed by real-time data) that enables teams to study scenarios for outage planning in the control room, as well as longer term future planning. Crucially in this context, it forms the base model which inputs into other online modelling tools such as PNA, OSA and NCMS.

5.2.2.4 Network Control Management System (NCMS)

Aiming to replace iEMS (integrated Energy Management System), NCMS delivers a real-time situational capability for control centre operators, enabling them to conduct real-time "what if" analysis. This system therefore presents a shift towards real-time updating of constraints. To achieve this, data is ingested from three primary sources:

- Static offline models from DNOs (Distribution Network Operators), TOs (Transmission Operators), OFTOs (Offshore Transmission Operators) and generators (submitted through OLTA) – this is the core of the model, providing a representation of the physical network,
- Dynamic, real-time metering data from SCADA,
- Dynamic, real-time data from 3rd parties (DNOs, TOs, OFTOs and generators), including physical flows, state of breakers etc.

5.2.3 Required Final Capability – High-Level Google X Report Interpretation

The required final capability discussed below interprets the description provided in Google X Tapestry's Advanced Dispatch Optimizer System Roadmap Report, providing a much greater level of detail, and highlighting arising decision points / considerations.

The description provided in the Tapestry report is relatively vague and lacks detail, thus requiring various assumptions to be made in the methodology. It consequently raises multiple questions and concerns, highlighted in the *considerations* sections below.

[Note: Whilst this section is included for completeness, an alternative "IBM view" of the final process is additionally outlined to give a detailed view which is free of assumption and addresses the relevant outlined considerations. Consequently, this section is relatively brief in discussion.]

The transmission model aims to provide both a view of active transmission constraints (thermal, contingency, voltage and stability) for the given time period in question, as well as suggestions for a resultant control strategy. In other words, the model aims to answer the question:

What are the forecasted active transmission constraints given recent loading trends, and what can we do about them?

The below figure provides an initial high-level assumed view of the overall process for implementing this multi-stage model.

5.2.3.1 Overview

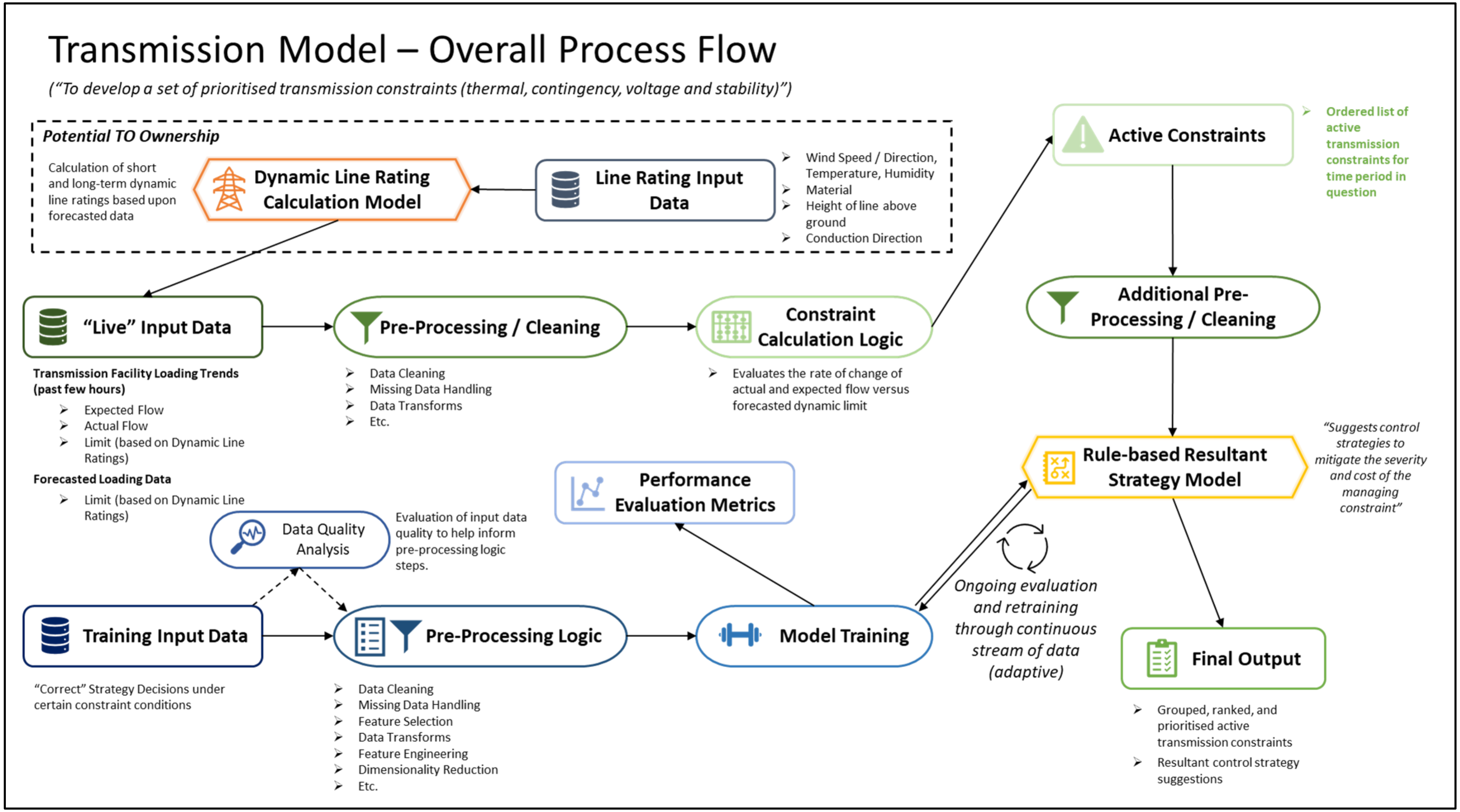

Figure 12: Transmission Model – Overall High-Level Process Flow

Briefly describing these stages:

Line Rating Input Data

Data attributes that influence a transmission line rating and can be used to calculate ratings dynamically. These include wind speed / direction, temperature, humidity, height of line, material, and conduction direction.

Dynamic Line Rating Calculation Model

Potentially owned by the Transmission Operators, this calculation unit outputs dynamic line ratings, thus aiding the calculation of constraints. Given the purpose of the constraint calculations is to analyse recent ("live") loading trends to foresee active transmission constraints, the dynamic line ratings required are both recent historic and forward-looking.

"Live" Input Data

This data, which is used to evaluate active transmission constraints, consists of transmission facility loading trends over the past few hours. This includes expected flow, actual flow, and established limits. Further, forecasted limits are also output from the Dynamic Line Rating Calculation Model.

Pre-Processing / Cleaning

An initial cleaning step ensures that the collected "live" input data is of a usable form and of sufficient quality to flow effectively into the constraint calculation logic. As indicated, steps may include, but are not limited to:

- Data Cleaning
- Missing Data Handling
- Data Transforms

Constraint Calculation Logic

The implemented logic takes the cleaned input data and evaluates the rate of change of actual and expected flow versus limit, as well as projecting forward against forecasted limits, to produce the Active Constraints output below. This takes the form of a short-term piece of data analysis, as opposed to a trained "model". In short, this aims to answer the question "*What constraint limits are projected to be reached?*".

Active Constraints

From the calculation logic, output is an ordered list of active transmission constraints for the time period in question. These provide a clear, detailed view that can be used to form control strategies.

Additional Pre-Processing / Cleaning

A further pre-processing / cleaning step may be required to ensure the constraints are able to flow into the resultant strategy model.

Training Input Data

To develop a rule-based model which can suggest suitable control strategies in response to a given set of transmission constraints, one requires training data indicating the "correct" strategy associated with given constraints. This is not trivial as the definition of "correct" may vary with individual opinion and risk appetite.

Data Quality / Correlation Analysis

This crucial first step evaluates the quality, format, and inter-relationships of variables in the available training data. The outcomes of the analysis help inform the usability of the data as well as dictate necessary Pre-Processing steps.

Pre-Processing Logic

Logic implemented here cleans and transforms data such that it can be used in the chosen model. As indicated, steps may include, but are not limited to:

- Data Cleaning
- Missing Data Handling
- Feature Selection
- Data Transforms
- Feature Engineering
- Dimensionality Reduction

Model Training

The exact nature of the modelling technique is dependent on the form of input data and the nuances of the problem. For example, an immediate question arising is:

Given a defined level of detail expected in the strategy outputs, is the decision-making process "modellable" such that a rule-based approach will be able to capture the nuances required?

Whether or not there is an objective "right answer" is an important consideration and should be used to inform the output format and modelling approach.

Ongoing Evaluation and Retraining through Continuous Stream of Data (Adaptive)

The purpose of Adaptive Machine Learning models (as opposed to Traditional Machine Learning) is to react to changing data sets, utilising real-time data to "adapt" and more accurately represent real-world situations. As such, there is an element of continuous improvement.

Performance Evaluation Metrics

Whilst the exact evaluation metrics cannot be specified before model definition, a form of accuracy calculation will likely inform model performance and parameter tuning.

Rule-based Resultant Strategy Model

The rule-based resultant strategy model aims to suggest suitable mitigation strategies given the set of input active transmission constraints. As indicated above, the complexity of this model is largely dependent on the level of nuance and complexity of strategies.

Final Output

The final output from this model group is the set of ordered active constraints combined with the resultant suggested control strategies. The potential form of this output is discussed below in sections 5.2.3.4 and 5.2.3.5.

5.2.3.2 Data Requirements Overview

The diagram above highlights three core sets of input data: Line Rating Calculation Inputs, "Live" Loading Trends, and Strategy Model Training Data.

Line Rating Calculation Inputs

As noted, this calculation would likely be owned by the Transmission Operator. The below data requirements are therefore provided simply for completeness as potential contributing variables.

The calculation inputs here aim to cover all attributes (both static and dynamic) that affect a transmission line's "dynamic line rating" at a given point in time. These can be readily split into static line properties, dynamic weather conditions, and dynamic operational attributes.

Feeding into the constraint calculations, these variables will need to cover a "recent historic" period in addition to a very short-term forward-looking timeframe (the reasoning behind this requirement is discussed below). The required frequency of dynamic variables is dependent on the line rating refresh rate needed, given the desired granularity of analysis.
[Note: Whilst, for this purpose, the focus is on the short-term forward and backward-looking periods as stated, the Dynamic Line Rating Calculation logic could in theory be utilised in isolation for any historic or forward-looking timeframe (assuming available input data).]

Table 10: Transmission Model – Line Rating Calculation Inputs

Category	Data	Description	Frequency	Total Time
Static Line Properties	Material	Transmission line material.	Static property	T-few hours through to T+1 hour.
	Height of Line / Line Sag	Average height of transmission line above ground level (affecting weather impact).	Static property	
Dynamic Weather Conditions	Wind Speed	Speed of wind, impacting temperature of transmission line.	Required refresh rate (TBD)	
	Wind Direction	Direction of wind, indicating parallel and orthogonal components.	Required refresh rate (TBD)	
	Temperature	Ambient temperature at line location.	Required refresh rate (TBD)	
	Humidity	Ambient humidity at line location.	Required refresh rate (TBD)	
Dynamic Operational Attributes	Conduction Direction	Direction of current flow.	Required refresh rate (TBD)	
	Etc.			

These variables account for the primary factors impacting line ratings in real time.

<u>"Live" Loading Trends</u>

Transmission facility loading trends over the past few hours, as well as forecasted dynamic limits, are input to a calculation module to generate the active transmission constraints (based upon forward projection of trends). As stated by Tapestry, this data is used to evaluate the rate of change of actual and expected flow versus limit.

Table 11: Transmission Model – "Live" Loading Trends Data

Category	Data	Description	Frequency (Recent Historic)	Total Time (Recent Historic)
Transmission facility loading trends	Expected Flow	Expected transmission flow over period (dependent on demand / generation forecasts).	To be set	Past few hours
	Actual Flow	Actual transmission flow over period.	To be set	
	Limit	Transmission limit at given time (dependent on the calculated Dynamic Line Ratings).	To be set	

The question of frequency of this recent historic data (spanning the past few hours) depends on the calculation logic to be implemented within the constraint calculation module. For example, a few sets of flow readings (expected vs. actual) covering the full several hour timeframes may be sufficient to establish a projected trend, but would likely miss the more subtle aspects incorporated by utilising a 10-minute frequency per se. Higher frequency readings would provide more detail though may be unnecessary given the relatively high-level of constraint definition.

In addition to the recent loading trends, the constraint calculation logic will use the forecasted dynamic line ratings output from the Dynamic Line Rating Calculation logic.

Table 12: Transmission Model – Forecasted Limits

Category	Data	Description	Frequency (Short-term Future)	Total Time (Short-term Future)
Forecast	Limit	Transmission limit at given time (dependent on the calculated Dynamic Line Ratings).	To be set	Subsequent hour.

Strategy Model Training Data

Regardless of the final form of the Resultant Strategy Model (see discussion above), training data must consist of a series of (historic) constraints and their associated "correct" mitigation strategies.

Table 13: Transmission Model – Strategy Model Training Data

Category	Data	Description	Frequency
Strategy Data	Sample Transmission Constraints	Set of example transmission constraint lists.	N/A – series of single point training examples.
	Associated "Correct" Mitigation Strategies	Set of mitigation strategies corresponding to the above constraint sets.	N/A – series of single point training examples.

Historic data pairs of this form would enable development of a rule-based model, suggesting "optimum" control strategies for a given set of constraints based upon the relationships learnt from the historic training data. As with many models of this type, a sufficient number[21] of example pairs covering an adequate range and complexity of situation would be required.

5.2.3.3 Data Models

As with the Adaptive Generation Models discussed above, we can create a logical entity-relationship diagram to visualise how the Line Rating Calculation inputs and Constraint Calculation inputs relate and could be structured.[22]

[21] The definition of "sufficient number" in this context is dependent on the level of variability and nuance in the underlying data population.
[22] See section 7 for overview of entity-relationship notation.

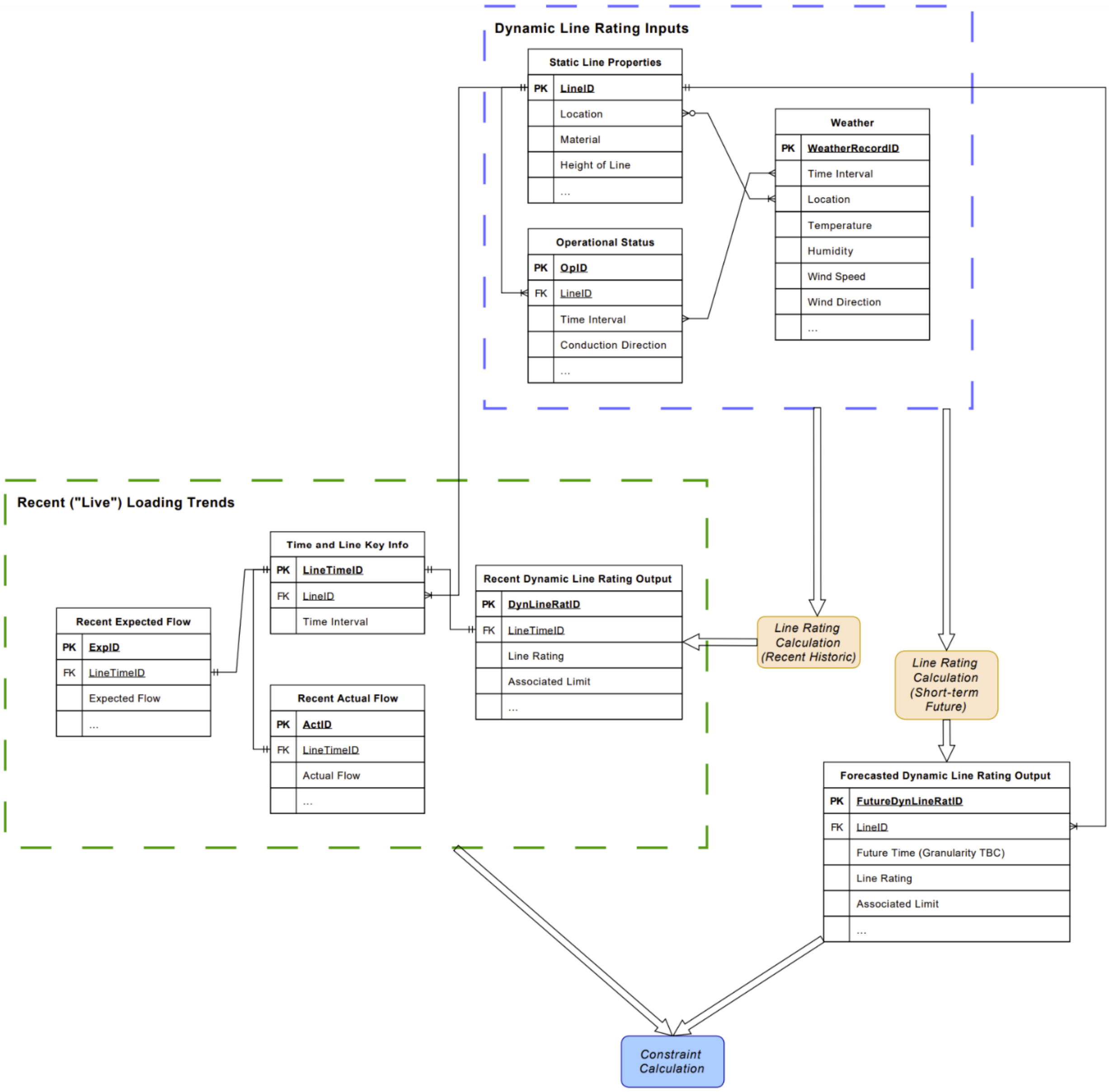

Figure 13: Transmission Model – Example view of data model for Line Rating Calculation inputs and Constraint Calculation inputs

Due to the complexity of the Transmission problem, this data model highlights calculation nodes in addition to the core underlying data inputs. As an example, the right-hand side of the model highlights how the line rating calculation logic outputs the required forecasted dynamic line ratings so they can flow into the constraint calculation. As before, the different connection types indicate the cardinality of data relationships.

5.2.3.4 Constraint Calculation Considerations

<u>Power Flow Modelling</u>

As noted in the below data availability comments, expected flow is dependent on a power flow run against the network model. In forming a solution of this type, one would have to consider where such power flow modelling should sit architecturally. For example, depending on other uses, the power flow modelling component may be best placed outside the Transmission data model architecture and called upon when required.

<u>Dynamic Line Ratings – Use of both "recent historic" and short-term forward-looking data</u>

When considering the above described process, a reasonable question arising may be:

Why are both short-term historic and short-term future dynamic line ratings required in the constraint calculation module? Could one instead only use the forward-looking ratings and compare against the projected flow trends?

Whilst this is not explicitly mentioned in the Google X Tapestry report, the suggested requirement for both short-term historic and short-term future dynamic line ratings stems from the evaluation of expected and actual flow over the past few hours. Use of corresponding calculated dynamic limits over the past few hours provides a view as to whether the dynamic line rating calculation effectively accounts for any discrepancy between expected and actual flow. This knowledge helps to establish the reliability of forecasted limits based upon the dynamic line rating logic. In other words, for a given circuit, it provides a view of recent accuracy of dynamic line rating.

<u>Use of Flow Trends</u>

One issue identified with the above process is the use of loading trend analysis to calculate transmission constraints. Whilst this may provide a useful view, use of this historic data implies the presence of an underlying organic trend. This may be an acceptable approximation when purely considering solar or wind generation, for example. However, in practice, the influence of additional factors results in trend movement that cannot be easily predicted through rate of change projection.

<u>Frequency of data</u>

The above tables do not specify the required data frequency / refresh rates. These are to be set based on levels of data availability as well as usefulness from a business insight point-of-view.

<u>Output Type</u>

This specification does not indicate whether the output constraints would take the form of constraint groups (as currently utilised) or more granular line-level constraints. Whilst there is significant benefit to the detail provided by line-level constraints, there is a balance to be struck between level of insight and computational requirement. As a result, it is likely that computational considerations will dictate the level of granularity.

5.2.3.5 Modelling Approach Considerations

As indicated above, the viability and potential form of the "Resultant Strategy Model" is dependent on the nuances of the problem being addressed as well as the definition of "Resultant Strategy".

The definition of “Resultant Strategy” here is currently unclear and, unless treated as an iterative version of an input forward-looking plan (requiring further inputs), has limited understood value. Does this simply refer to suggested alternative flow routes associated with each constraint? Or is there more capability expected from this part of the model?

Different constraints often need to be managed using different levers. For example, some constraints are best managed by “moving” generation (e.g., reduction of wind generation in Scotland and corresponding increase of thermal generation in the South of England), whilst others may be best managed through alternative routes (including, in the future, demand side response). This leads to a complex view of potential strategies.

Deterministic “Correct” Strategy

One approach to this problem would be to develop a model that outputs a single “correct” strategy to mitigate a given set of transmission constraints. The core concerns arising with regards training a deterministic model of this type are:

- How subjective is a view of “correct” strategy?
- What additional factors impact strategy choice?
  [e.g., total demand profiles etc. – these would have to be built into the model to improve accuracy.]
- Assuming required additional factors can be modelled, is the decision-making process actually “modellable” via a rule-based approach? Or is every scenario unique and hence cannot be easily generalised?

Multiple Suggestion Output

Another approach might look to output a series of potential strategies to aid the manual decision-making process. This would enable operators to utilise their knowledge of the specific scenario and any associated nuances to make a more informed decision around strategies. This approach appears more sensible at this stage due to the unknown complexity of scenarios and level of experience / intuition utilised in manual decision-making.

5.2.4 Data Availability Comments

Whilst the main Transmission model discussion lies within the *Required Final Capability – IBM View* section, some data availability points are highlighted below.

Line Rating Calculation Inputs

Dynamic ratings are to be owned by the Transmission Operator (TO) going forward. As such, any required data for these calculations falls outside the remit of the ESO Control Room activities.

"Live" Loading Trends

Table 14: Transmission Model – "Live" Loading Trends Data Availability Comments

Category	Data	Description	Total Time (Recent Historic)	Comments
Transmission facility loading trends	Expected Flow	Expected transmission flow over period.	Past few hours	Expected flow will come from generation and load forecasts. Once applied against the network model and a power flow run with the future network conditions, this would provide a view of future flows.
	Actual Flow	Actual transmission flow over period.		Comes from the actual metering from the TO.
	Limit	Transmission limit at given time (dependent on the calculated Dynamic Line Ratings).		To be done by the TO going forward (see above).

Strategy Model Training Data

"Correct" strategy data for given conditions is not held, other than what is put into the transmission plan. The current idea is to look at this in line with the look ahead view to observe the effect of a generator on a constraint given the metric to be optimised (e.g., cost).

5.2.5 Required Final Capability – IBM View

As indicated previously, a more exact and detailed vision of a final capability is additionally included here. This view addresses the concerns highlighted in the above interpretation and does not require the same level of assumption.

To provide greater granularity of insight, the final vision presented here splits analysis by the 11 constraint problem types (as defined as part of Balancing Transformation)[23]. For each of these problems, we have conducted a multi-dimensional analysis to establish relative importance and associated complexity if included in the optimiser. Treating the problems separately allows for an appreciation of the differences in frequency, magnitude of problem, impact on dispatch solution etc., and, subsequently, the significant differences required in approach.

Whilst these problems are addressed individually below, the overall Transmission Input Data model is the collection of such sub-models – together ensuring the “highest value” problems are addressed in the optimiser, whilst considering the balance between value add and computational complexity.

5.2.5.1 Constraint Type Analysis

Multi-dimension analysis was conducted with ESO SMEs to establish the relative importance of the 11 defined constraint problem types. This analysis enabled constraint types to be ranked and differentiated, subsequently resulting in a more comprehensive vision which treats constraint types individually[24].

For each of these constraint problem types, there are three core options regarding how they could be addressed in an end vision:

1. *As-Is* – address the constraint type separately to the optimisation problem, utilising the current (manual) approach,
2. *Post-Process Automated Check* – rather than incorporating the constraint type into the optimiser itself, create an automated check of the optimiser generated solution and make any required changes manually,
3. *Inclusion in the Optimiser* – include the constraint type in the formulation of the optimisation problem.

Which of these options is chosen for each constraint type is dependent on the relative impact they have on the problem – striking a balance between frequency of problem occurrence, ease of final process for control room engineers, and associated complexity of the optimisation problem.

[23] Thermal Constraints, Generator Stability, Voltage (SQSS), Fault Level, Regional Response, Rate of Change of Frequency (RoCoF) / Inertia, Vector Shift, Largest Loss, Frequency Impact, Black Start, National Load

[24] Constraint models are considered in isolation here, though there will clearly be some dependencies between different constraint types when considered from a holistic optimisation perspective.

For example, if any of the constraint types were to introduce quadratic (or indeed higher order) polynomial constraints, this would drastically change the complexity of the optimisation problem and may be better incorporated via options 1. or 2. above.

The below table provides this initial analysis of constraint type relative impact and subsequent focus areas from an optimisation perspective.
[Note: A suggested next step would be more detailed analysis of these constraint types to validate the conclusions drawn here as to optimiser-suitability.]

Constraint Type Definitions

As mentioned above, analysis is split based on the 11 constraint problem types defined as part of Balancing Transformation:

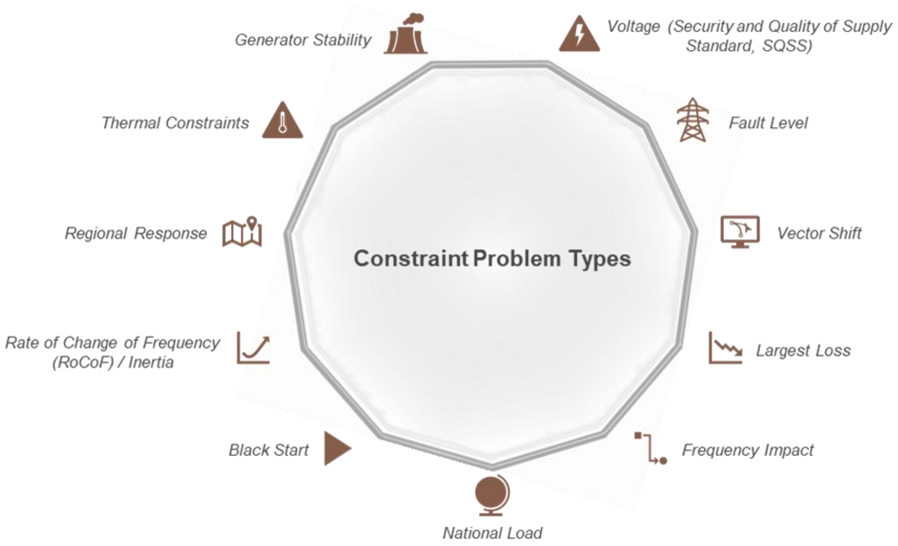

Figure 14: Constraint Problem Type Graphic

Definitions of the various constraint problem types are as follows:

Table 15: Constraint Problem Type Definitions

Constraint Problem	Description
Thermal Constraints	The MW flow through a line is limited by thermal factors. If a line is too hot, it starts to drop and risks breaching the safety clearance. Factors such as weather impact the line temperature and hence the associated MW flow limit. Thermal constraints most frequently occur when one of two lines trips, resulting in increased reliance on the other. The transmission team are responsible for identifying impacted lines and post-fault actions, but the energy team is required to select the necessary units to perform said actions.

Generator Stability	These constraints ensure that a Generation unit does not trip or disintegrate in the event of a fault. They are shown as a limitation of MW flow through a certain line for a given amount of time, or alternatively a rule dictating which units can (or indeed must) be online.
Voltage (Security and Quality of Supply Standard, SQSS)	The concern usually considered here is voltage drops. Voltage is dependent on reactive power and on the structure of the electrical network (configuration, outages, repair, etc.). Voltage issues are addressed by running the "correct" generators based upon reactive power and geographical spread.
Fault Level	At a high-level, a fault occurs when a line is touching something that it should not be, creating a short circuit and resulting in a high current. If the current is too high, one is unable to clear the fault (the automatic switch to stop power flow fails). Fault level calculates how high the current would be if there was a fault. The transmission team runs a simulation on all possible faults and provides the requirement to put a unit on or off to solve bad values.
Regional Response	There are two core considerations around regional response constraints: 1. May want to limit response within a constraint area because, if they were all activated, a constraint limit might be crossed, 2. May want to avoid having response in the same circuits as large generators to mitigate the impact of a circuit break – loss of the generator would still enable access to the response.
Rate of Change of Frequency (RoCoF) / Inertia	"RoCoF" describes how fast frequency values change. Frequency increases or decreases at a rate proportional to the gap between generation and demand. Inertia also impacts the RoCoF. If the RoCoF is too high, certain embedded generation units trip, resulting in a RoCoF event. This most likely occurs after a largest loss. As NG pay generators to protect their units to prevent tripping, the relative size of this issue should decrease. RoCoF is required to be below 0.125Hz/s at all times. Usually, the cheapest option to achieve this is to change the size of the largest loss, but this only works up to a certain point and further considerations such as inertia may be required.
Vector Shift	Small renewable units connected to the distribution network disconnect themselves from the grid if they notice changes in the angle of the voltage. This angle changes in the case of a transmission fault (line tripping) or a largest loss in order to protect them from breakage. This is a local problem and possible severity is dependent on, for example, circuit relations between embedded generation and larger generators.

Largest Loss	Sufficient response is carried to ensure that frequency can be recovered within the required timeframes in the case of a "largest loss" system event. In other words, answering the question "What is the theoretical largest amount of MW that could be lost in the case of a system event?". There is a largest generation loss and a separate largest demand loss, both of which are dependent on multiple factors.
Frequency Impact	As an additional consideration to ensure impact on frequency is not forgotten, one should also ask "Given inertia etc., how would loss of a given generator impact frequency?".
Black Start	Certain generators are able to start with no power requirement, whilst others are paid to continue generation on a very low level for several hours post a system-outage. At every point in time, NG require black start machines to be available in every zone to assist in the case of a national blackout.
National Load	National and regional demand is volatile, with the variability of both weather and consumer behaviour affecting this. As such, forecasts may be incorrect and result in a significant discrepancy compared to actuals.

<u>Constraint Type Relative Analysis</u>

The below analysis evaluates each of the defined problems against a series of dimensions, including frequency, impact on solution, associated workload etc., to establish whether they should be considered within the optimiser.

Table 16: Constraint Problem Type Analysis (Note: 1=Low, 3=High)

Constraint Problem Type	How frequently does the problem occur? (1-3)	How sub-optimal is the resultant solution (i.e., how far from the cost optimum?) (1-3)	How much additional workload does each occurrence create for the control room? (1-3)	Is the constraint type currently handled by an optimiser? If yes, which one?	Is the constraint type handled by UWA? If yes, which one?	Can the constraint type likely be formulated as a MILP constraint?	Likely focus of input data model?
Thermal Constraints	3 Not uncommon to have 3-4 constraints active per day.	TBC	3	Yes LDA and MDA, elements going into BDO as restrictions.	No	Yes	Yes
Generator Stability	2 Often have a limit whether it's a thermal or	TBC	3	Yes LDA and MDA, elements going into	No	Yes	Yes

	stability constraint			BDO as restrictions.			
Voltage (SQSS)	3 Effectively occurs every night and some days due to insufficient reactive power and the market not highlighting voltage as a problem to solve.	3 Significant sums of money are spent on running units with the sole purpose of addressing voltage. All asset types are eligible though require correct network spread.	3 Effectively requires a complete replan to ensure voltage needs are met.	No Big unit sync /desync decisions are already fixed once the optimiser starts running.	**No complete** Voltage sheet from the TSM states what the requirement is. There is a sheet showing location of the unit for visualisation.	**Yes** This was one of the aims of EBS (scheduling).	**Yes**
Fault Level	1	1 Mostly solved by transmission running arrangement.	1	No	No Handled by OLTA	**Unsure**	No
Regional Response	1 Used to be large as contracted a lot of response in one area.	2	1	No	No Done on paper.	**Yes**	No
Rate of Change of Frequency (RoCoF) / Inertia	3 At least daily, mostly depends on wind and interconnectors.	3 Have to run assets that provide sufficient inertia; raising the question "could an optimiser come up with a significantly better solution?"	3 Strategy team. 2 Energy team.	No Optimiser does not look at scheduling time period.	**Yes** FFRIC/DELPHI	**Yes** Scheduling timeframe.	**Yes** Though just automating it may be sufficient, as an optimiser might not produce a drastically better solution.
Vector Shift	1 Risk is assessed continually with FFRIC and DELPHI, but real impact is quite low.	1	1	No	**Yes** FFRIC/DELPHI	**Yes**	No

Largest Loss	3	1 Drives the solution as a necessary requirement to meet.	2	No	Yes FFRIC/DELPHI	Yes	Yes
Frequency Impact	3 Very similar to largest loss.	1	2	No Set requirement.	Yes FFRIC/DELPHI	Unsure	No
Black Start	1	1	1	No	Yes Daily check by aNSE if they have enough (restoration contracted) units in place in each zone.	Yes Scheduling timeframe.	No
National Load	3	1 Input requirement rather than a deviation from optimum.	3	Yes LDA, MDA	Yes Only the demand forecasting part.	Yes	Yes

Summarising the numerical values to highlight severity of problem,

Table 17: Constraint Problem Type Analysis - Numerical Attribute Summary

Constraint Problem Type	Frequency of Problem	Sub-optimality of Resultant Solution	Additional Work per Occurrence	Average
Thermal Constraints	*High*		*High*	*High*
Generator Stability	*Mid*		*High*	*Mid*
Voltage (SQSS)	*High*	*High*	*High*	*High*
Fault Level	*Low*	*Low*	*Low*	*Low*
Regional Response	*Low*	*Mid*	*Low*	*Low*
RoCoF / Inertia	*High*	*High*	*Mid*	*High*
Vector Shift	*Low*	*Low*	*Low*	*Low*
Largest Loss	*High*	*Low*	*Mid*	*Mid*
Frequency Impact	*High*	*Low*	*Mid*	*Mid*
Black Start	*Low*	*Low*	*Low*	*Low*
National Load	*High*	*Low*	*High*	*Mid*

Here, the colours denote the severity of the different constraint problems when measured against the three headings. Simply translating the numerical scores from the analysis table above, colours range from green (score of 1) through to red (score of 3).

The resulting "highest value" problem types forming the initial group for inclusion in the optimiser logic are:

1. Thermal Constraints
2. Generator Stability

3. Voltage
4. RoCoF / Inertia / Largest Loss

For each of these specific problem types, we now look to create a view of the potential data model flow into the optimiser module.

5.2.5.2 Overview

Based on the constraint type analysis above, the below diagrams show the processes by which the relevant constraints (those to be fed into the optimiser) could be calculated. Note that these take the form of constraint calculation modules, aiming to output constraints based on forecast data (as opposed to explicitly built Machine Learning models).

Together, these individual sub-models (each representing a different constraint type problem) combine to form the overall proposed Transmission Input Data model.

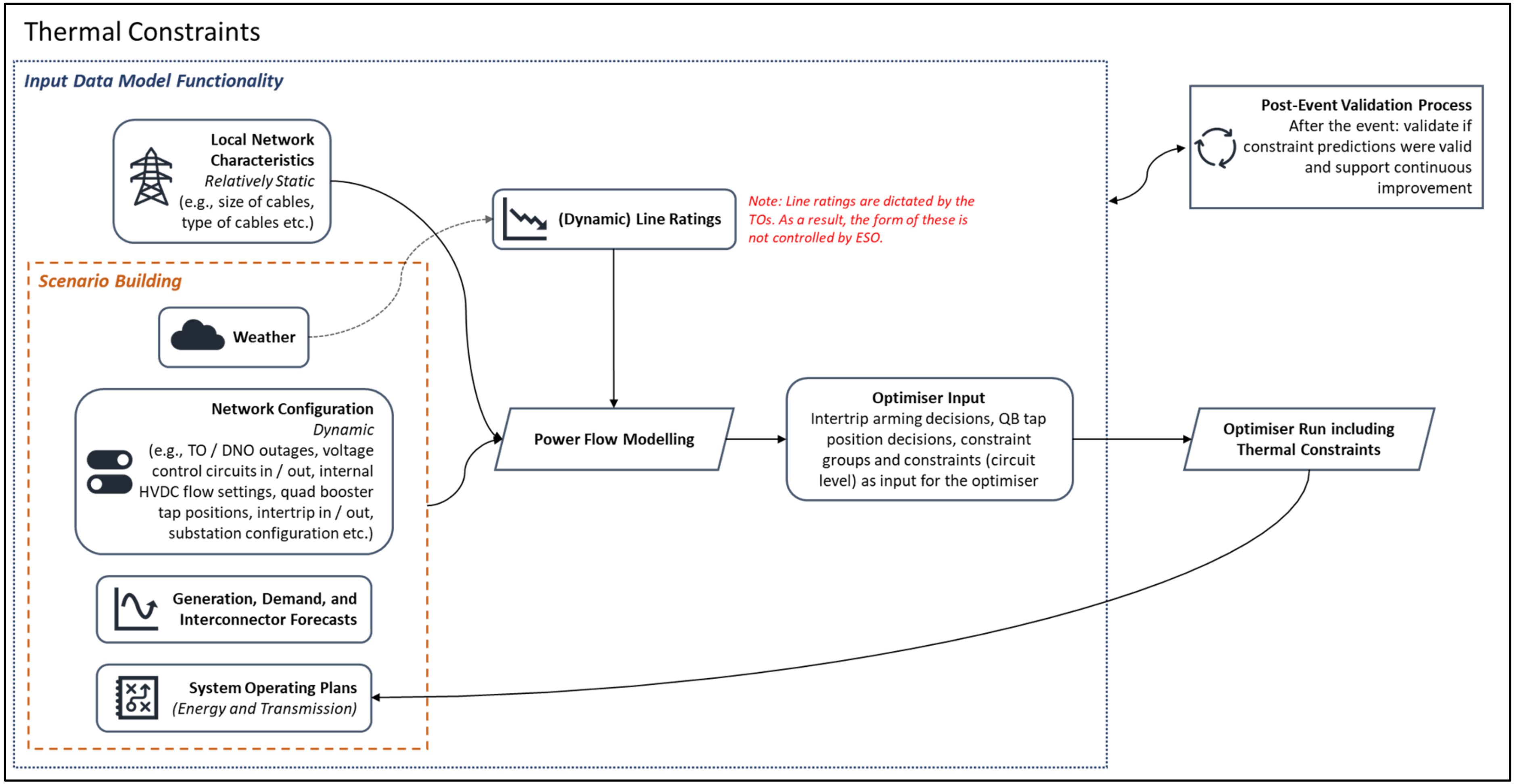

Figure 15: Transmission Model – Thermal Constraints

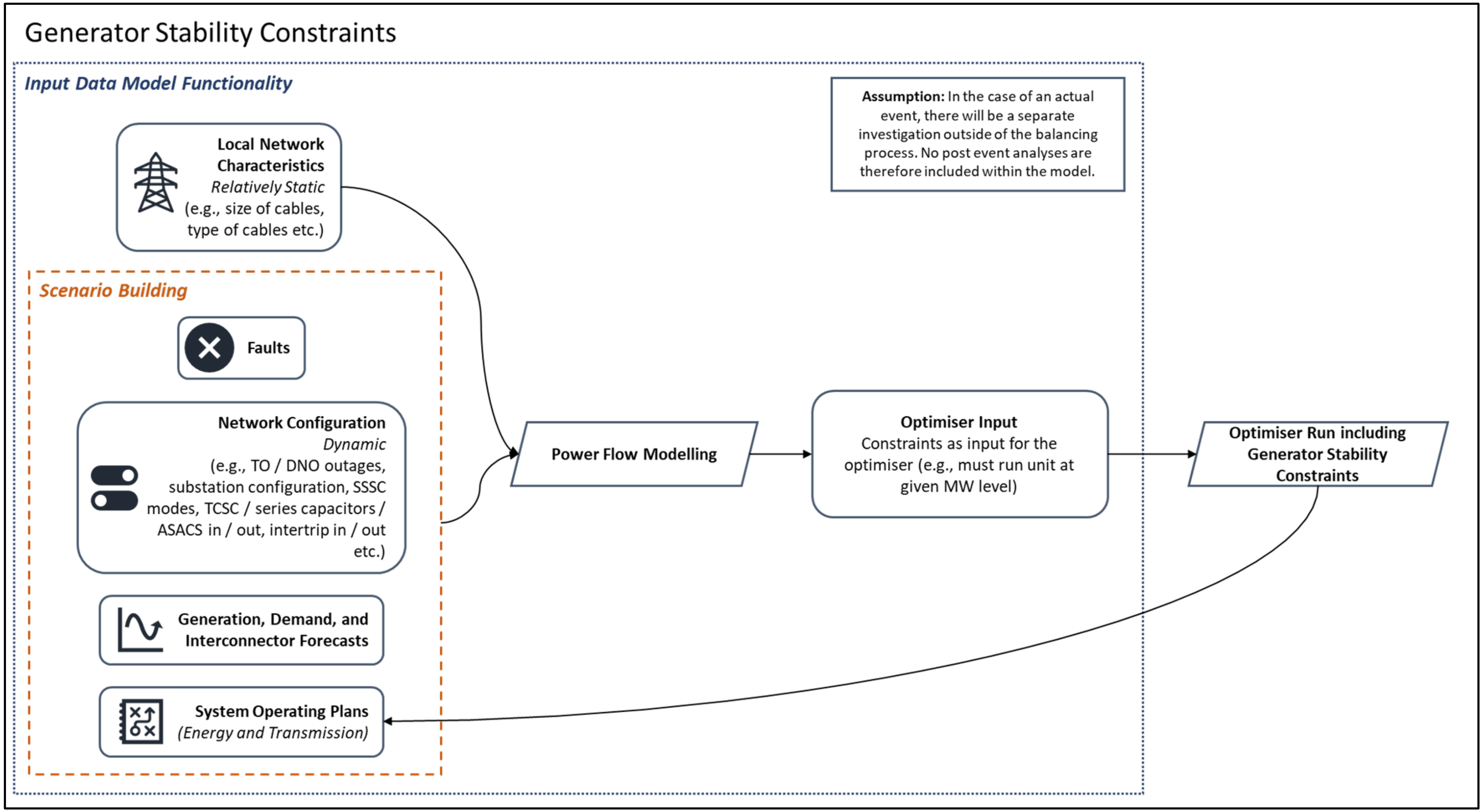

Figure 16: Transmission Model – Generator Stability Constraints

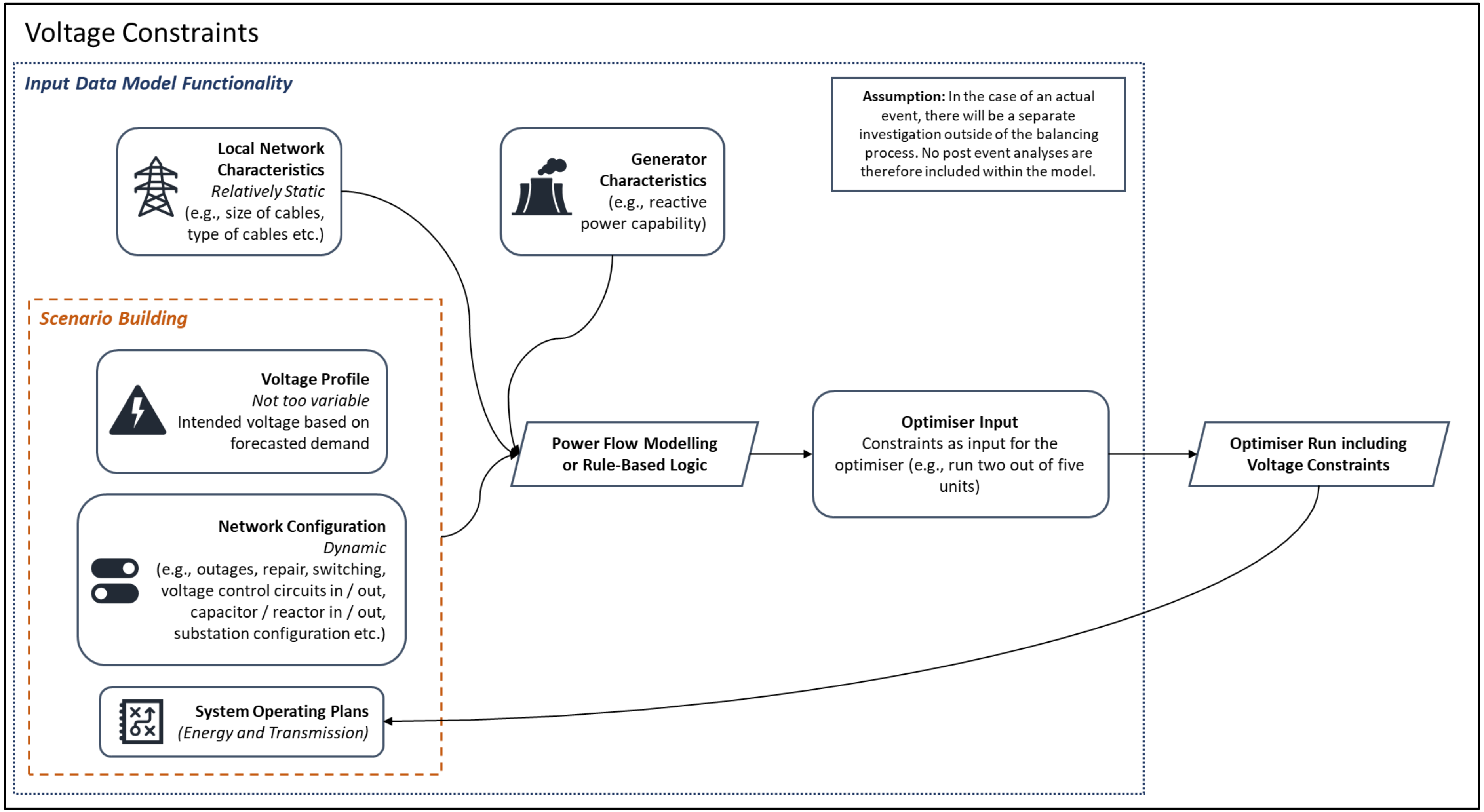

Figure 17: Transmission Model – Voltage Constraints

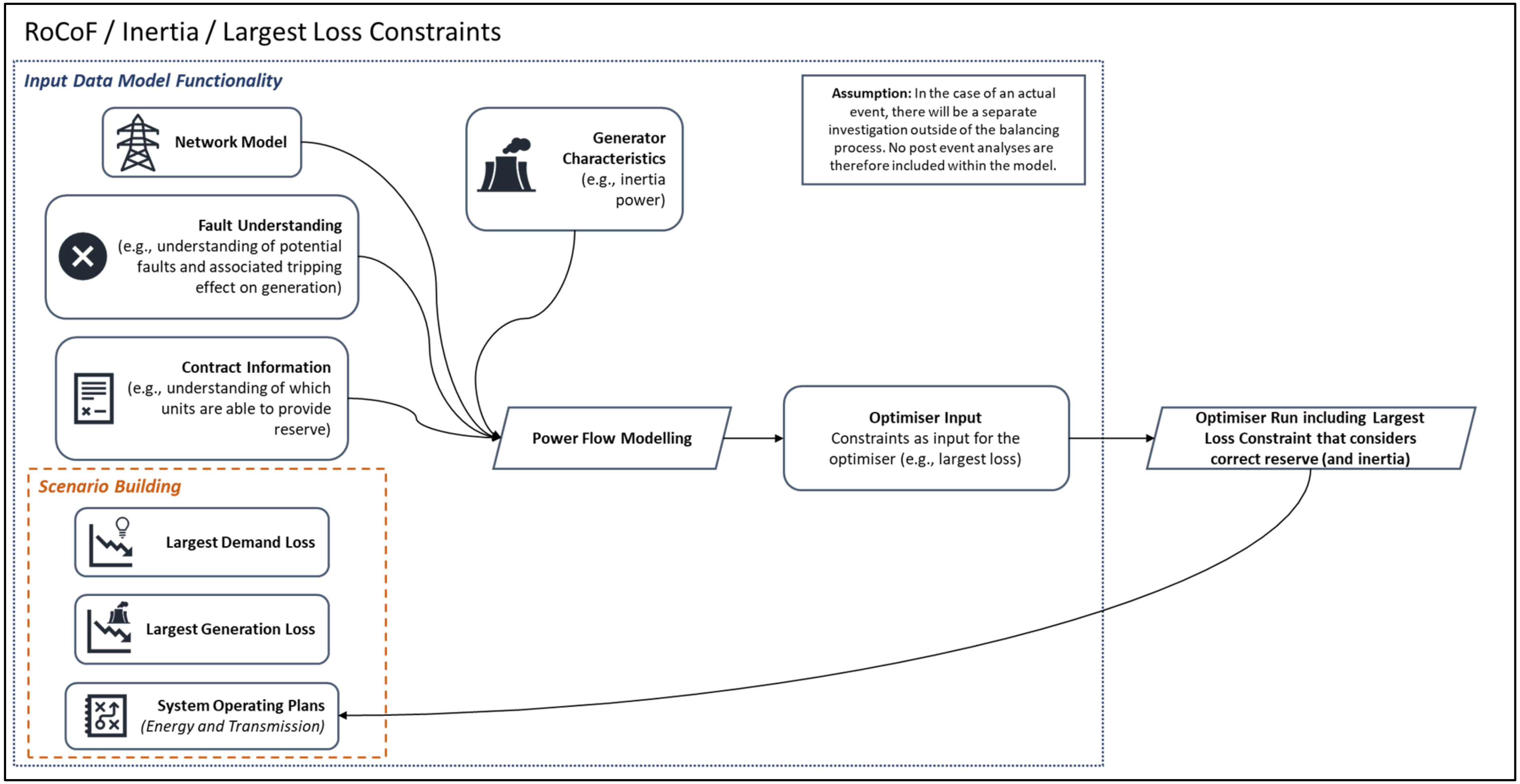

Figure 18: Transmission Model – RoCoF / Inertia / Largest Loss Constraint

Exploring each of these in turn:

Thermal Constraints

Thermal constraints are generated by feeding a series of relevant data metrics into a power flow modelling component. These include local network characteristics and line ratings, as well as controllable variables that make up the scenario testing capability. Altering the input weather forecasts, network configuration, generation / demand forecasts, or system operating plans will provide insight as to the sensitivity of constraint outputs to these particular dimensions.

The Transmission Operator (TO) ownership of line ratings (be these static or dynamic) removes a potential calculation complexity for ESO in developing this model architecture. However, as noted, the associated lack of control over the format, inputs, refresh frequency etc. could arguably hinder the intended granular analysis. [See below for further discussion.]

As shown, a post-event validation process is crucial here in creating a feedback loop of continuous learning and model improvement. The working assumption is that this process would be enabled by a data warehouse holding information on relevant decisions and production plans for a given time period to allow post-event analysis by various groups. This process is therefore not currently considered in scope for the control room.

Generator Stability Constraints

Similar to thermal, generator stability constraints here make use of power flow modelling to create the required optimiser input. Data inputs for the power flow model include relatively static local network characteristics, and the controllable variables which form scenarios to test. Scenario data consists of faults being tested, network configuration, generation / demand forecasts, and system operating plans. Forming of these scenarios can indicate relative sensitivity of output constraints to input variables, as previously.

Unlike thermal constraints, a post-event validation process is not explicitly referenced here. In its place is an underlying assumption regarding the post-treatment of genuine events: *In the case of an actual event, there will be a separate investigation outside of the balancing process. No post event analyses are therefore included within the model.*

Voltage Constraints

Voltage constraints are generated by running relatively static local network characteristics and generator characteristics, as well as the building blocks of a given scenario through power flow modelling (or indeed simpler rule-based logic). A scenario is created from a given voltage profile, network configuration, and set of system operating plans. Sensitivity analysis can be carried out by running a series of different scenarios.

Actual voltage events are very rare and, similarly to generator stability, it is assumed that post-event investigations will be held outside the balancing process, with no need for such analysis within the modelling capability.

RoCoF / Inertia / Largest Loss Constraints

RoCoF / inertia and largest loss constraints (for input into the optimiser) are created in a very similar manner to one another, again utilising power flow modelling. [Note: These constraint types are not currently calculated using power flow modelling, but this type of capability is planned for the development and rollout of NCMS.] The number of inputs shown is fairly large comparatively to other constraint types: network model, generator characteristics, understanding of faults, contract information regarding reserve, and scenario variables. The scenarios in this instance consist of largest demand loss, largest generation loss, and system operating plans. Output constraint sensitivity analysis can be conducted as previously.

Post-event investigations and analyses are again assumed to be held outside the scope of this work.

5.2.5.3 Data Requirements Overview

The above process diagrams highlight the multiple sources of data required for each of Thermal, Generator Stability, Voltage, and RoCoF / Inertia / Largest Loss Constraints.

Mirroring the constraint process diagrams, data sources are split into fixed / externally sourced data and scenario building variables. Altering of these scenario variables (e.g., weather forecast, network configuration etc.) enables a view of constraint sensitivity to input variables.

Thermal Constraints

Table 18: Thermal Constraints – Data Requirements

Category	Data	Description	Frequency	Total Time
Relatively Static / Externally Owned Data Sources	Local Network Characteristics	Relatively static characteristics of the network (e.g., size of cables, type of cables etc.).	Desired refresh frequency (at discretion of model user provided data sources can support choice).	Forecast for future period of interest.
	(Dynamic) Line Ratings	Dynamically calculated line ratings, based upon temperature, wind speed / direction, conduction direction, line sag etc.		
Scenario Building Data	Weather	Weather variables, including temperature, wind speed / direction etc.		
	Network Configuration	More variable network elements, such as TO / DNO outages, voltage control circuits in / out, internal HVDC flow settings, quad booster tap positions,		

		intertrip in / out, substation configuration etc.		
	Generation, Demand, and Interconnector Forecasts	Forecasts for generation, demand and interconnector flow.		
	System Operating Plans	Both energy and transmission system operating plans.		

As indicated in the process diagram, line ratings are to be created and shared by the Transmission Operators, and as such are categorised as an externally owned data source.

Generator Stability Constraints

Table 19: Generator Stability Constraints – Data Requirements

Category	Data	Description	Frequency	Total Time
Relatively Static / Externally Owned Data Sources	Local Network Characteristics	Relatively static characteristics of the network (e.g., size of cables, type of cables etc.).	Desired refresh frequency (at discretion of model user provided data sources can support choice).	Forecast for future period of interest.
Scenario Building Data	Faults	Faults to be tested.		
	Network Configuration	More variable network elements, such as TO / DNO outages, substation configuration, SSSC modes, TCSC / series capacitors / ASACS in / out, intertrip in / out etc.		
	Generation, Demand, and Interconnector Forecasts	Forecasts for generation, demand and interconnector flow.		
	System Operating Plans	Both energy and transmission system operating plans.		

Voltage Constraints

Table 20: Voltage Constraints – Data Requirements

Category	Data	Description	Frequency	Total Time
Relatively Static / Externally Owned Data Sources	Local Network Characteristics	Relatively static characteristics of the network (e.g., size of cables, type of cables etc.).	Desired refresh frequency (at discretion of model user provided data sources can support choice).	Forecast for future period of interest.
	Generator Characteristics	Relevant generator characteristics, e.g., reactive power capability.		
Scenario Building Data	Voltage Profile	Intended voltage profile based on forecasted demand.		
	Network Configuration	More variable network elements, such as TO / DNO outages, substation configuration, SSSC modes, TCSC / series capacitors / ASACS in / out, intertrip in / out etc.		
	System Operating Plans	Both energy and transmission system operating plans.		

RoCoF / Inertia / Largest Loss Constraints

Table 21: RoCoF / Inertia / Largest Loss Constraints – Data Requirements

Category	Data	Description	Frequency	Total Time
Relatively Static / Externally Owned Data Sources	Network Model	Required network model.	Desired refresh frequency (at discretion of model user provided data sources can support choice).	Forecast for future period of interest.
	Generator Characteristics	Relevant generator characteristics, e.g., inertia power.		
	Fault Understanding	Understanding of potential faults and associated tripping effect on generation.		
	Contract Information	Understanding of which units are able to provide reserve.		

Scenario Building Data	Largest Demand Loss	Largest demand loss, as usually defined.		
	Largest Generation Loss	Largest generation loss, as usually defined.		
	System Operating Plans	Both energy and transmission system operating plans.		

5.2.5.4 Architectural / Modelling Considerations

Power Flow Modelling

As explicitly noted in the above process diagrams, the proposed high-level architecture requires suitable power flow modelling for all constraint types. It is assumed that this requirement is not a limitation, due to existing capability and plans around NCMS. However, should this present an issue, one would have to carefully consider how power flow modelling integrates into the final solution.

Line Rating Ownership

As noted multiple times above, it is assumed going forward that line ratings (either static or, preferably, dynamic) will be wholly owned by the Transmission Operator (TO) and therefore not in scope for ESO operations. These line ratings are considered a crucial element of the thermal constraint calculations, and establishing a reliable connection to a trustworthy data source is therefore very important.

TO-calculated line ratings may be considered more reliable, though this obviously places the ESO one-step removed from data generation. As such, there are associated considerations in the *Explainable AI* space (see below).

Constraint Groups vs. Circuit-Level Constraints

As noted above when discussing the *High-Level Google X Report Interpretation*, any future vision concerning transmission constraint modelling must consider whether the current "constraint group" approach is the most appropriate form of output.

The most obvious alternative would be a more detailed, granular approach – outputting a set of specific circuit / line-level constraints to adhere to. Conversely, due to the current effectiveness and usability of constraint groups, there would be no acknowledgeable benefit in looking to shift to an even higher level of aggregation above those. The two realistic options are therefore constraint groups or the more detailed circuit-level constraints.

There appears to be widespread appreciation that more granular constraints would provide benefit through additional insight. However, one limiting factor is the associated computational requirement. Aggregation to constraint groups provides a less computationally intensive view which can be more easily managed in an optimisation environment.

Post-Event Validation Processes

A post-event analysis module is only explicitly included for the (comparatively very regular) thermal constraint type events. This supports continuous improvement of the calculations by establishing if the generated constraints were valid. However, as noted, the relevant data should be stored and accessible to various groups, and this post-event analysis module does not necessarily sit within the control centre capability[25].

As described above, for the other (rarer) constraint type events, a post-event analysis of this type is considered to be out of scope for the control room balancing process, and thus not included in the input data models. Instead, a (likely more manual) investigation is expected to be carried out elsewhere post an actual event.

Data Relationships to the Optimiser(s)

The design of the optimiser modules will determine the exact form of required input types. Architectural questions arising at this stage focus on whether just the constraints will be fed into the optimiser (as implied in the above process diagrams), or whether additional data such as network characteristics should also be inputs.

5.2.5.5 Scenario Testing Capability and Output

As indicated in the process diagrams, there is intended to be a scenario building capability for each of the explored constraint problem types. This would enable a view of constraint output sensitivity to various forecasted inputs.

A more holistic view of scenario testing considerations to ensure consistency across multiple models is explored within the Architecture deliverable.

5.2.6 Data Gap Analysis

As is to be expected when defining a new, innovative capability, none of the existing or planned processes completely meet the requirements outlined in "Required Final Capability". However, mapping said requirements to existing data sources and techniques provides a clearer view of missing elements, as well as next steps.

As noted previously, the true gap analysis deliverable sits separately to this report, and the below section therefore comments only on data availability and quality.

[25] *"The working assumption is that this process would be enabled by a data warehouse holding information on relevant decisions and production plans for a given time period to allow post-event analysis by various groups. This process is therefore not currently considered in scope for the control room."*

5.2.6.1 Overview

The level of maturity observed in the existing transmission constraint calculations means that, comparatively to other areas, the data gap is small. Primary focus lies on the ownership and required quality / granularity of external data sources (e.g., dynamic line ratings).

5.2.6.2 Availability of Data

Without the requirement for multiple years of training data, the Transmission models are ***not subject to the historic data availability issues observed in other areas.***

Further, the majority of data inputs are either relatively static, externally owned, or assumed to flow from other models / ESO systems. Given the level of work already completed in the Transmission space, ***no significant data availability issues are anticipated***.

Table 22: Transmission Models (All Explored Problem Types) – Input Data Availability

Category	Data	Time	Currently Understood Availability
Relatively Static / Externally Owned Data Sources	Local Network Characteristics	Forecast for future period of interest.	Available, (relatively) static information.
	(Dynamic) Line Ratings		Assumed to be created and owned by the TOs. [Pending conversation regarding ownership and required frequency, granularity, format etc.]
	Generator Characteristics		Available, (relatively) static information.
	Network Model		Available and utilised.
	Fault Understanding		Assumed SME knowledge.
	Contract Information		Available, (relatively) static information.
Scenario Building Data	Weather		Forecast data available and utilised.
	Network Configuration		To be set as part of scenario building.
	Generation, Demand, and Interconnector Forecasts		Assumed to be available from other models within the overall architecture.
	System Operating Plans		Produced and utilised.
	Faults		To be set as part of scenario building.
	Voltage Profile		Produced and utilised.
	Largest Demand Loss		Produced and utilised.

	Largest Generation Loss		Produced and utilised.

5.2.6.3 Data Quality / Granularity Analysis

As before, data has not been able to be extracted for IBM-run data quality analysis, with comments instead reflecting the current understanding of relevant data quality and granularity.

There are no known significant data quality issues in this area, in part due to the relatively static or user-defined nature of many of the data sources. Unknown factors for consideration include:

- The agreed quality and granularity of any TO-produced dynamic line rating data – this must strike a balance between the ideal modelling level and feasibility based upon line rating calculation complexity / input data.
- The accuracy and granularity of current weather forecasts for scenario building. The detailed technical definition of the individual problem type models will inform the necessary requirement.

5.2.7 Regulatory Considerations, Explainable AI, and Process Impacts

As with the other modelling areas, implementation of such a final vision methodology raises points for consideration around explain-ability etc.

5.2.7.1 Dispatch Instructions

As for all Input Data models, the previously discussed principles around the ability for humans to understand, analyse, and improve the underlying dispatch instruction logic apply here. In the case of Transmission, arising questions for scrutiny may include:

- In situations where the lowest price units are not utilised, what are the underlying reasons? Is there, for example, a particular binding transmission constraint altering the optimum solution? To what degree are said transmission constraints altering the optimum solution? Are the generated transmission constraints accurate?

Regarding accuracy of constraints, some of these questions may be answered by the post-event validation processes described above.

5.2.7.2 Line Rating Ownership

Given the line rating TO ownership model discussed above, the quality and availability of line rating data sits outside of ESO's responsibility. In order to cover the full landscape of *Explainable AI* considerations, there requires a level of transparency around the input data and processes involved in producing the line ratings. This likely requires a contractual change to the ESO relationship with the TOs, ensuring that this level of transparency is achieved.

5.2.7.3 Impact on Roles and Processes

As further noted by the ESO Operational Manager[26] with regards the Transmission elements, any proposed models of the above types will require significant changes in existing processes and role responsibilities. These should clearly be considered carefully when planning development and incremental implementation stages.

"*The TAEs processes are likely to change depending on what transmission optimisation is done within the SCED and what needs to be set up through the Adaptive Transmission modelling. The TSEs are also likely to be involved in these processes as well. The TSM will also be involved as they will need to agree the short-term transmission plan.*"

5.2.8 Next Steps

The separately delivered "Roadmap" output will specify next steps in working towards the more holistic longer-term end vision.

However, key next steps highlighted above include:

1. More detailed analysis of the 11 constraint types to validate the optimiser-suitability conclusions drawn. As detailed above, this analysis would categorise the constraint types into the *As-Is*, *Post-Process Automated Check*, and *Inclusion in the Optimiser* groups.
2. Discussion with TOs regarding the ownership, format, and required frequency of dynamic line ratings.
3. Initial Data Science workstream activities (see 4.2.1).

[26] *Virtual Energy System - Advanced Dispatch Optimiser Google X Comparison (April 2022)*

5.3 Adaptive Interconnector Models

5.3.1 Overview

The Adaptive Interconnector Models described by Google X Tapestry in the output document Advanced Dispatch Optimizer System Roadmap Report have a single primary output:

- Probabilistic scenario testing capability to forecast the likely interconnector flows under a variety of potential conditions.

The idea behind this capability is to provide operators with more accurate forecasts of interconnector flow and capabilities, thus aiding dispatch decision-making.

The detail around this specification is given in the "Required Final Capability" section below, with particular focus on this scenario testing capability and associated options (as previously).

The interconnector model sections below aim to outline some of the current and planned interconnector forecast capabilities, detail the final vision (highlighting any decision points for consideration), and discuss some comparative gaps. [Note: The main As-Is analysis and gap analysis sit within a different deliverable but relevant data points are discussed here.]

5.3.2 Existing and Planned Capabilities

[See As-Is deliverable for full overview.]

Below is an overview of some relevant elements but, as noted above, the true As-Is analysis sits separately to this report, and as such the below is far from exhaustive.

This process-flow diagram provides a high-level view of the current trading process, noting the relationships between the ESO control room, ESO trading team, and trading counter parties.

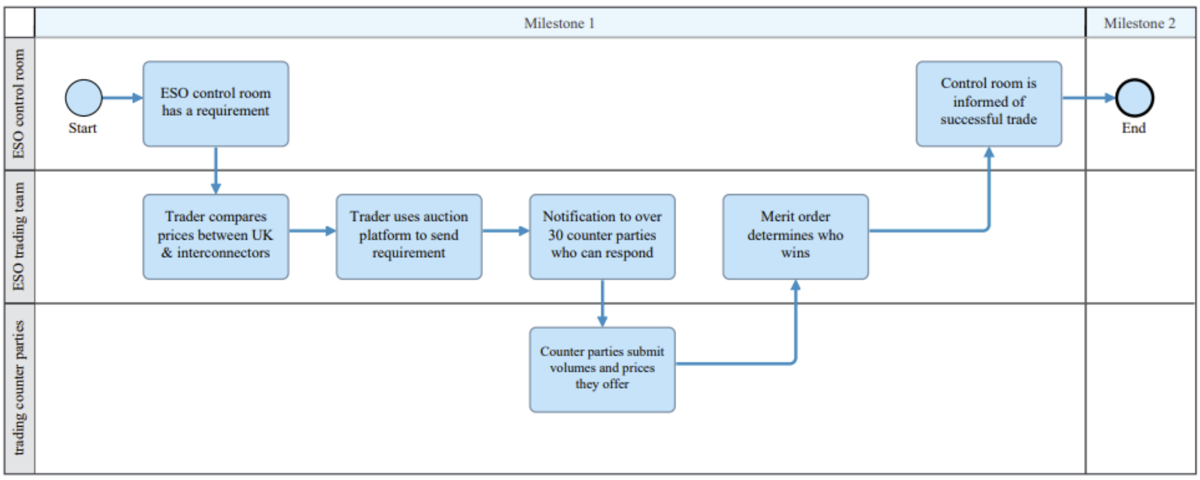

Figure 19: Blueworks Live – Interconnector Trading Process

Briefly, interconnectors are currently modelled in both online and offline analysis tools (PNA and OLTA, respectively). However, these are modelled as static generators, as opposed to full High-voltage DC (HVDC) models.

Power Network Analysis (PNA)

As detailed more thoroughly in the Transmission model section above, PNA is a real-time analysis tool that uses a real-time flow of data to generate a view of current system conditions (State Estimation). It then runs a series of contingencies based upon this. With focus on real-time, no forecast data is used within PNA.

Offline Transmission Analysis (OLTA)

At a high level, OLTA is an offline network study model (i.e., it is not fed by real-time data) that enables teams to study scenarios for outage planning in the control room, as well as longer term future planning.

Crucially in the context of future data models, neither of these existing systems is used to forecast interconnector flows. At present, interconnector flows (export to the continent) are not considered as part of forecast demand, but prediction of flows is of interest to the trading team with regards anticipating any commercial actions.

A final utilised tool within the interconnector space is AMIRA. Unlike the tools detailed above, AMIRA is a third-party capability and hence the underlying methodology etc. is not owned and controlled by ESO.

AMIRA

AMIRA is a third-party tool used by the control room and interconnector trading team. It is used to forecast interconnector output changes due to relative GB vs. non-GB price changes and provides the associated forecast error probability. This is the only digital tool that the ESO uses to forecast interconnector flows.

Whilst this tool is arguably useful in the absence of any other forecasts, feedback suggests that predictions are often incorrect and are not generally trusted.

5.3.3 Required Final Capability

The required final capability discussed below interprets the description provided in Google X Tapestry's Advanced Dispatch Optimizer System Roadmap Report, providing a much greater level of detail, and highlighting arising decision points / considerations.

Of all the adaptive input models highlighted in the Tapestry report, this model group has the shortest dedicated description, at just 11 lines. Consequently, as before, multiple assumptions are required to form a full interpretation.

Further, Tapestry notes that "*To our knowledge, no such adaptive interconnector modelling approach has been implemented by a Grid Operator*", thus emphasising the innovative nature of this element.

The interconnector model aims to provide a view of predicted (half-hourly[27]) interconnector flow under given scenario conditions. This considers real-time flows, scheduled interconnector flows, flow trends, and market conditions. In other words, the model aims to answer the question:

Given a prescribed set of forecasted scenario conditions, what is the forecasted actual flow on the interconnectors (prior to any further required reactive manual trading / intervention post-optimiser run)?

The below figure provides an initial high-level view of the overall process for implementing this model.

[27] As before, half-hourly is the minimum temporal granularity required. Interpolating for shorter steps within the dispatch process would likely provide further beneficial insight.

5.3.3.1 Overview

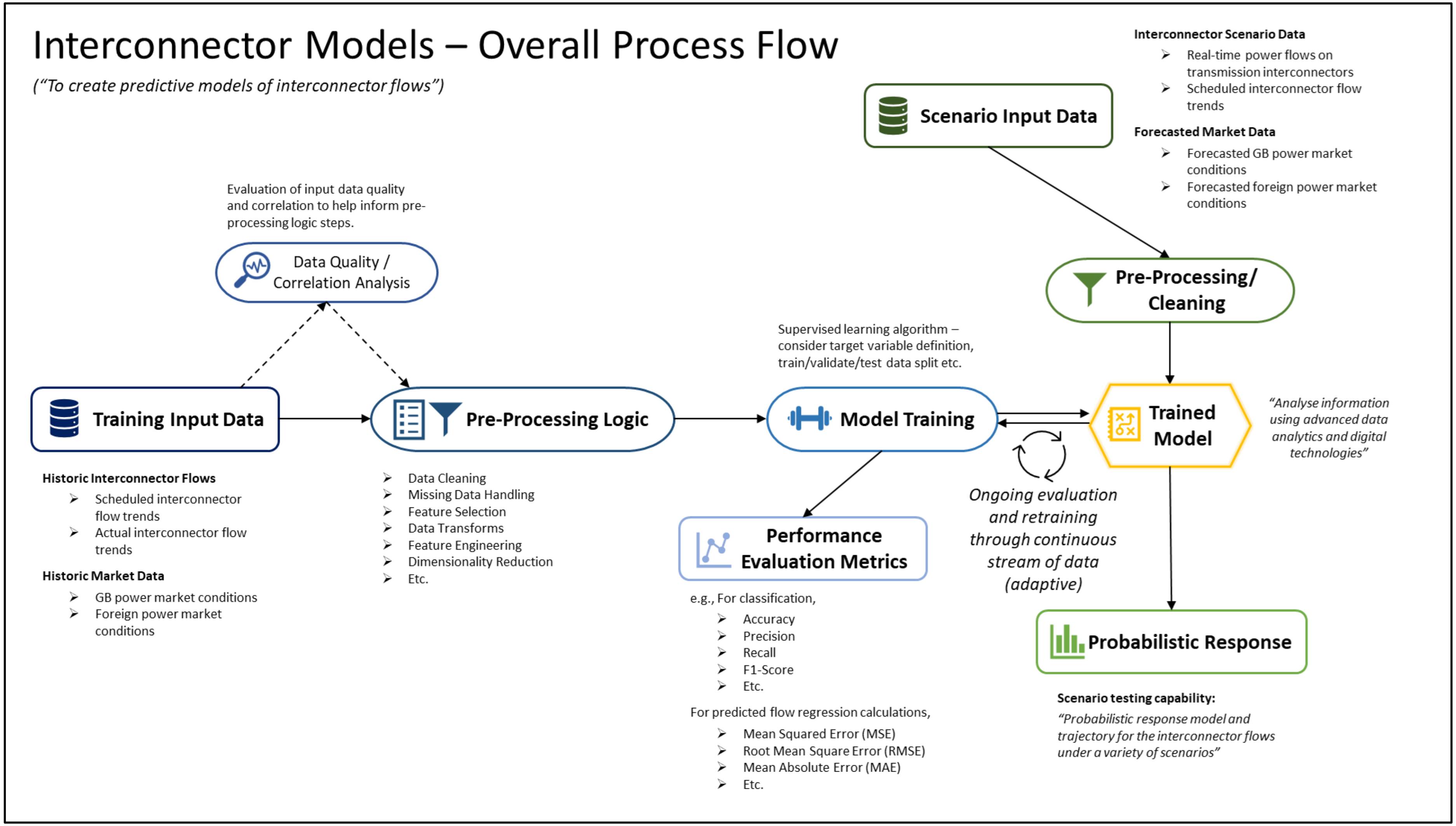

Figure 20: Interconnector Models – Overall High-Level Process Flow

For a brief description of these process stages, see section 5.1.3.1.

The model in question uses supervised learning techniques to predict the actual (half-hourly) interconnector flow, for each interconnector, under given scenario conditions.

Considerations around the form of the model output, as well as the final output from potentially running multiple scenario tests to account for uncertainty in the forecasted input variables, are discussed at length in sections "Modelling Approach Considerations" and "Scenario Testing Capability and Output". These sections explore the possibilities of probabilistic base models (as opposed to point estimates) and probabilistic outputs from scenario testing[28].

5.3.3.2 Data Requirements Overview

Within the process flow shown, data requirements can broadly be split into two categories: Historic Training Data and Scenario Input Data. Potential data sources are discussed in the data availability section.

Historic Training Data

Training data refers to the set of historical (labelled) data that will be used to train the first iteration of the model. Said training data will later be updated over time in line with a defined re-training schedule.

The training data for this model consists of Historical Interconnector Flows (i.e., *What has happened previously with regards scheduled vs. actual interconnector flow?*) and Historic Market Data for analysis (i.e., *How have changing market conditions affected the interconnector flows?*).

Table 23: Interconnector Models – Training Data

Category	Data	Description	Frequency	Total Time
Historical Interconnector Data	Scheduled interconnector flow trends*	Scheduled flow profile of electricity across the various interconnectors over time.	Half-hourly (for each dispatch interval)	At least 1 year, preferably approx. 3 years.
	Actual interconnector flow trends	Actual flow of electricity across the various interconnectors over time.	Half-hourly (for each dispatch interval)	
Historic Market Data	GB Market Data	GB energy market prices, volumes and associated trends.	Half-hourly (for each dispatch interval)	

[28] As noted previously, when viewed through a holistic architectural lens, the scenario-based approach provides consistency across the model types and enables coherent testing of output sensitivity to conditions (see Architecture deliverable).

	Foreign Market Data	Foreign energy market prices, volumes and associated trends.	Half-hourly (for each dispatch interval)	

*Note: In order to train the model with realistic scheduling timeframes, the core focus for corresponding scheduled variables will be at point x minutes before actual, where x represents the time before real-time at which the model would be run in practice.

As previously, there is a balance to be struck between model accuracy and data gathering complexity. It is important to remember that further re-training will be continuous as more data is collected, thus improving the accuracy of the model.

Scenario Input Data

Scenario Input Data here refers to the set of information fed into the trained model to produce the probabilistic output desired. What the model requires as input is a set of forecasted data covering the power market conditions as well as interconnector information.

In other words, for the given future time in question, the model input data consists of, for each interconnector, Interconnector Scenario Data (i.e., *What are the current and scheduled flow trends to be investigated?*) and Forecasted Market Data (i.e., *How do we expect the market factors affecting flow trends to be behaving over the time in question?*).

Table 24: Interconnector Models – Scenario Input Data

Category	Data	Description	Time
Interconnector Scenario Data	Real-time power flows on transmission interconnectors	Real-time power flows across the interconnectors at point of model run.	Given time period in question.
	Scheduled interconnector flow trends	Scheduled flow profile of electricity across the various interconnectors.	
Forecasted Market Data	GB Market Data	GB energy market prices, volumes and associated trends.	
	Foreign Market Data	Foreign energy market prices, volumes and associated trends.	

[Note: Given the number of variables, the scenario definition process itself could exist as a separate problem. Management of this is briefly discussed in the below section “Scenario Testing Capability and Output”, as well as within the Architecture deliverable.]

5.3.3.3 Data Models

The below logical entity-relationship diagrams provide a view of how both the scenario input data sources, and separately the training data sources, could relate and be structured.[29]

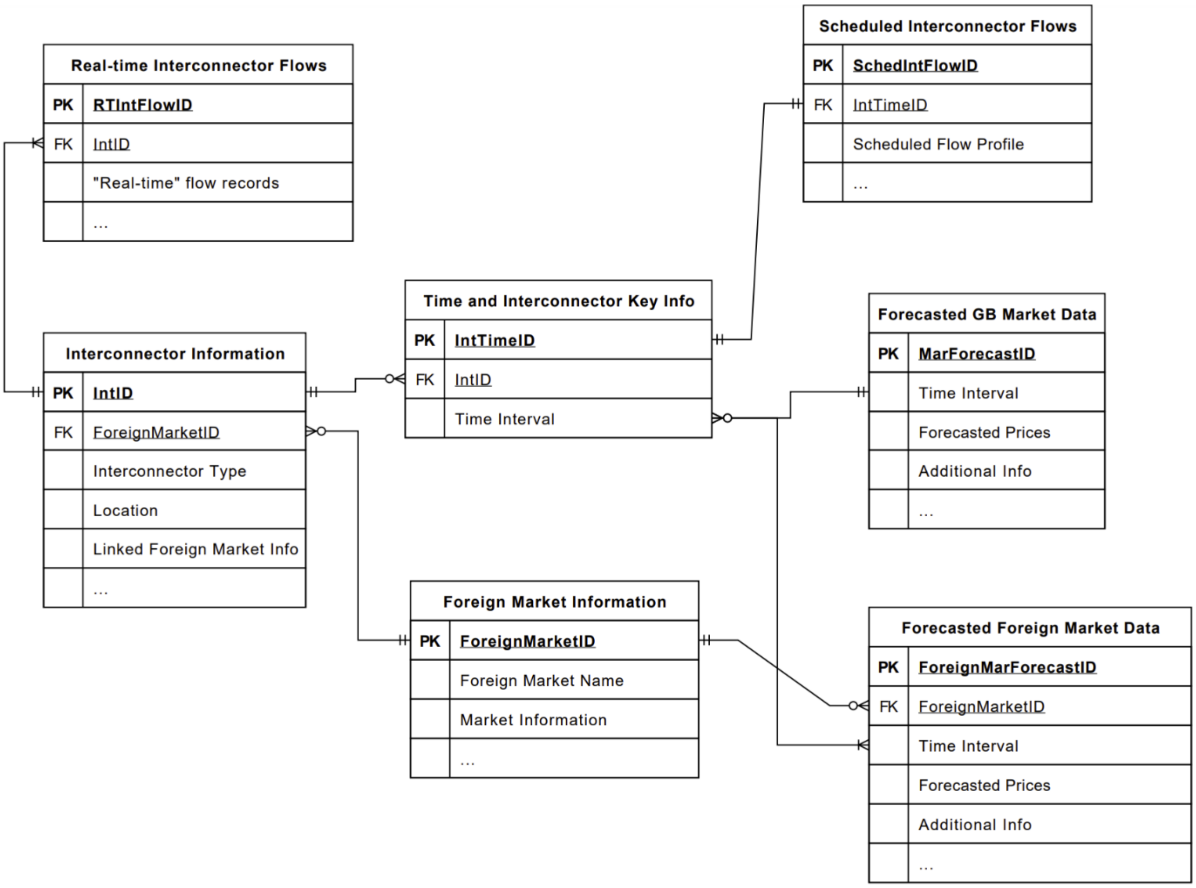

Figure 21: Interconnector Models – Example view of data model for scenario input data sources

This model exemplifies the relationships between the different data sources and provides a practical view as to one way the end vision data structures could be realised.

As an example, the scheduled interconnector flows are linked via a key to the specific interconnector ID and time interval being trialled. Shown by the connection types in the above diagram, each set of scheduled flows will join to precisely one Interconnector / Time Interval combination key. The interconnector ID can then be further used to gather additional information about the interconnector such as related foreign market etc.

Similarly for the listed historic training data:

[29] See section 7 for overview of entity-relationship notation.

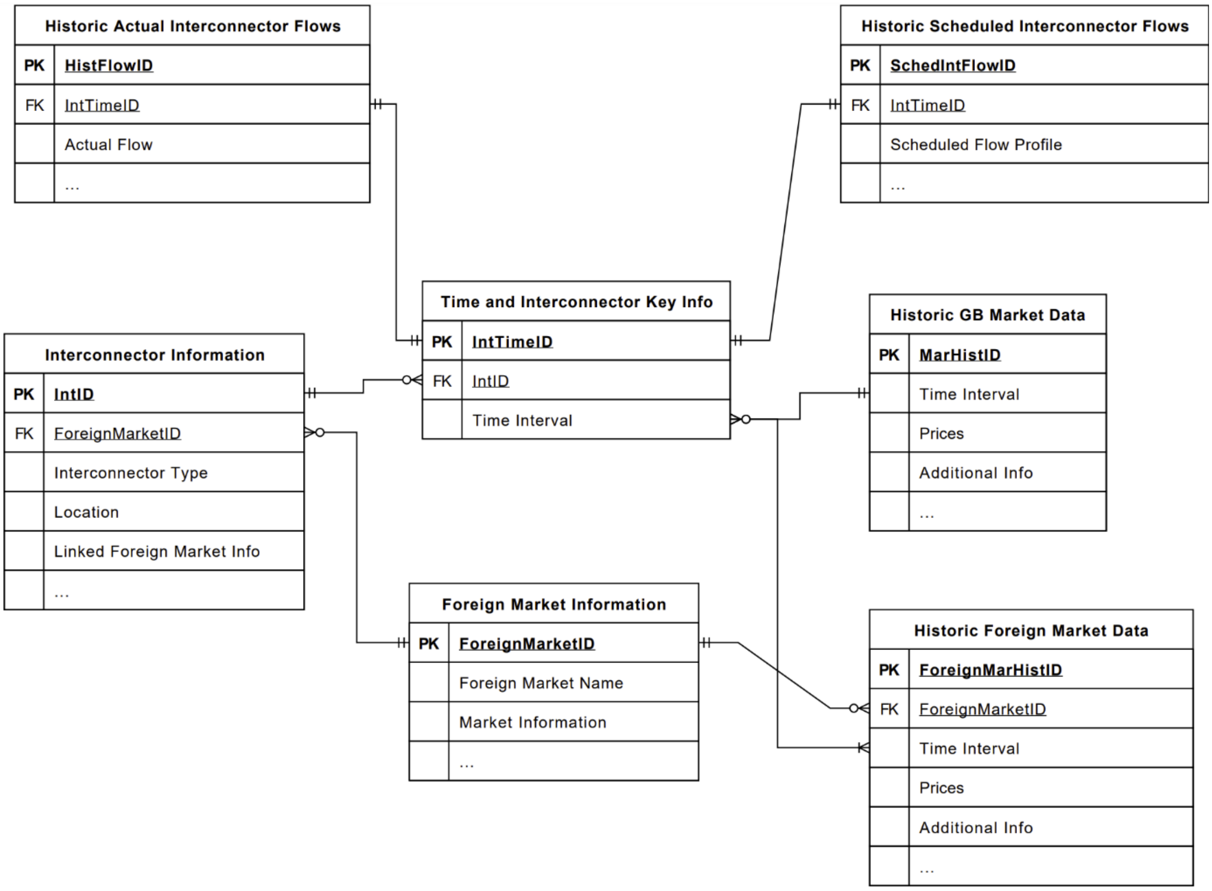

Figure 22: Interconnector Models – Example view of data model for training data sources

5.3.3.4 Modelling Approach Considerations

Due to the similar problem structure and model type, the considerations outlined in the Generation Models section (Regression vs. Classification and Deterministic vs. Probabilistic) are also valid here. To avoid repetition, please refer to section 5.1.3.4 for definition and discussion of these points.

<u>Considerations for Interconnector Input Data Models</u>

An equivalent algorithm matrix to that produced for Generation Models is shown below.

Deterministic Regression	**Deterministic Classification**
Predicting a single numerical value (or profile from a series of points) for actual flow across the different interconnectors for each half-hour interval, given a set of input conditions.	*Predicting a single class (group) value for actual flow across the different interconnectors for each half-hour interval, given a set of input conditions.*
Probabilistic Regression	**Probabilistic Classification**
Giving a probability distribution across numerical values for actual flow across the different interconnectors for each half-hour interval, given a set of input conditions.	*Giving a probability distribution across class (group) values for actual flow across the different interconnectors for each half-hour interval, given a set of input conditions.*

Figure 23: Interconnector Models – Matrix of modelling techniques

5.3.3.5 Scenario Testing Capability and Output

As with the modelling approach, the considerations arising around running of the scenario testing capability (deterministic single run vs. deterministic multi-run vs. probabilistic single run etc.) are identical to those discussed in section 5.1.3.5. These are therefore not repeated in full here.

However, equivalent views of sample parameter spaces and distribution output from a deterministic multi-run approach are shown below.

Table 25: Interconnector Models – Example parameter space for scenario testing

Category	Data Type	Parameter	e.g., Discrete Range	e.g., Distribution
Interconnector Scenario Data	Real-time power flows on transmission interconnectors	Real-time measured flows on a given interconnector (MW)	N/A – measured value	N/A – measured value
	Scheduled interconnector flow trends	Scheduled flow trend for a given interconnector – likely taking the form of a series of (time, MW value) pairs	For the given time unit, [900, 950, ...]	For the given time unit, $\Delta \sim \mathrm{N}(1200,150)$
	Etc.			
Forecasted Market Data	GB Market Data	Forecasted cost profile for GB generation – likely taking the form of a	For the given time unit, [1.00, 1.15, ...]	For the given time unit, $\vartheta \sim \Gamma(2,1)$

		series of (time, £/MWh value) pairs		
		Etc.		
	Foreign Market Data	Forecasted cost profile for foreign market import – likely taking the form of a series of (time, £/MWh value) pairs	For the given time unit, [1.00, 1.15, ...]	For the given time unit, $\vartheta \sim \Gamma(2,1)$
		Etc.		

[Note: example discrete ranges and distributions are purely illustrative.]

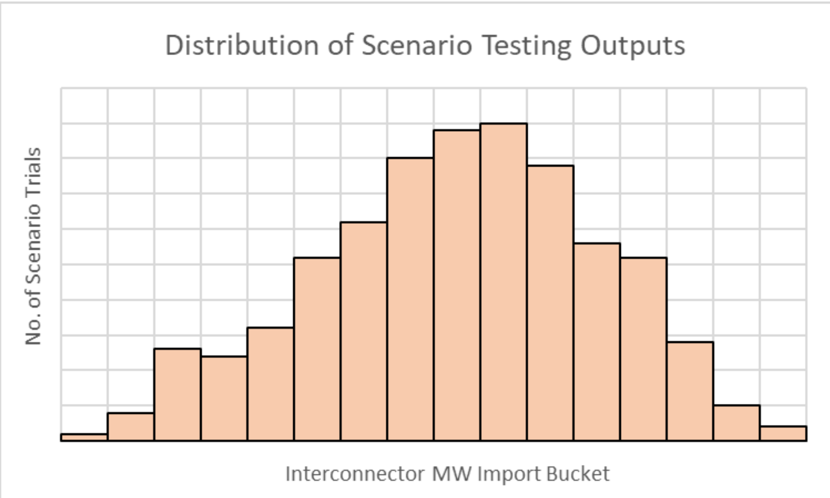

Figure 24: Interconnector Models – Example distribution output from running multiple trials with a deterministic model

5.3.4 Data Gap Analysis

As is to be expected when defining a new, innovative capability, none of the existing or planned processes completely meet the requirements outlined in "Required Final Capability". However, mapping said requirements to existing data sources and techniques provides a clearer view of missing elements, as well as next steps.

As noted previously, the true gap analysis deliverable sits separately to this report, and the below section therefore comments only on data availability and quality.

5.3.4.1 Overview

Forecasting of interconnector flows is inherently difficult due to its dependency on market movements (see discussion in 5.3.6 below). As a result, an approach of this type is relatively experimental, and the required data is not necessarily available and / or at the correct level of granularity.

5.3.4.2 Availability of Data

The below tables provide an overview of the currently understood data availability gap.

Historic Training Data

Most elements of the historic training data are available in some form (perhaps requiring purchase). The next stage of analysis would be to establish data quality and whether or not these datasets are of sufficient granularity for the given model purpose.

Table 26: Interconnector Models – Training Data Availability

Category	Data	Frequency	Total Time	Currently Understood Availability
Historical Interconnector Data	Scheduled interconnector flow trends	Half-hourly (for each dispatch interval)	At least 1 year, preferably approx. 3 years.	Historic scheduled flows available. *Arising question: Are scheduled plans from, e.g., day-ahead timescales sufficient for this purpose?*
	Actual interconnector flow trends	Half-hourly (for each dispatch interval)		Publicly available data through multiple sources (e.g., 5-minute frequency dating back to 2016 via Elexon[30]).
Historic Market Data	GB Market Data	Half-hourly (for each dispatch interval)		Historic data not currently explicitly held but theoretically available (perhaps requiring purchase). *Note: Just the final values would likely not provide sufficient levels of granularity for a given time period.*
	Foreign Market Data	Half-hourly (for each dispatch interval)		Historic data not currently explicitly held but theoretically available (perhaps requiring purchase).

[30] https://bmrs.elexon.co.uk/interconnector-flows

				Note: Just the final values would likely not provide sufficient levels of granularity for a given time period.

Scenario Input Data

Availability of the Scenario Input Data "Additional" variables is inherently related to the above availability of Training Data. The difference arises in the time horizon being considered, with Training Data being historical and Scenario Input Data being forward-looking.

Whilst some variables are readily available, the ***limited forecasting of market conditions may lead to difficulty in defining relevant, accurate scenarios.***

Table 27: Interconnector Models - Input Data Availability

Category	Data	Time	Currently Understood Availability
Interconnector Scenario Data	Real-time power flows on transmission interconnectors	Given time period in question.	Real-time flow data is measured, recorded, and displayed live in the control room.
	Scheduled interconnector flow trends		Default plans exist for each interconnector based upon day-ahead prices.
Forecasted Market Data	GB Market Data		*Whilst a range of scenarios could simply be created and tested, there is limited market forecasting to base these on.* Market data of this type is not explicitly forecasted, with traders instead using their experience / intuition when observing trends. Pricing of forward products provides an indication of expected market movement – however, the UK market is not particularly liquid, making this more difficult.
	Foreign Market Data		*Whilst a range of scenarios could simply be created and tested, there is limited market forecasting to base these on.* Market data of this type is not explicitly forecasted, with traders instead using their experience /

			intuition when observing trends. Pricing of forward products provides an indication of expected market movement – foreign markets are often more liquid than the UK, making this more realistic as an indicator.

5.3.4.3 Data Quality / Granularity Analysis

As before, internal data has not been able to be extracted for IBM-run data quality analysis, with comments instead reflecting the current understanding of relevant data quality and granularity.

Actual Interconnector Flows

Historic actual interconnector flows are available at 5-minute frequency from present back to 1st January 2016 via Elexon[31], with real time data uploaded with a lag of approximately ten minutes. This dataset covers the interconnectors:

- Belgium (Nemolink)
- Eleclink (INTELEC)
- France (IFA)
- IFA2 (INTIFA2)
- Ireland (East-West)
- Netherlands (BritNed)
- North Sea Link (INTNSL)
- Norther Ireland (Moyle)

MW values are given to the nearest integer. This data is considered to be of sufficient granularity for the purposes listed.

Forecasted Market Data

As mentioned above in the availability comments, any forecasted market data is generally considered to be of poor quality and accuracy, with traders relying mainly on intuition. The arising question regarding these data sources is:

Can forecasted market data accuracy be significantly improved to a usable level (e.g., using different input data, modelling techniques etc.), or does the inherent sporadic nature of the market set an accuracy ceiling below usable level?

The answer to this question is dependent on the definition of "usable level" of accuracy. Additionally, answering the question thoroughly would require a separate data science project to find the likely accuracy ceiling.

[31] https://bmrs.elexon.co.uk/interconnector-flows

Further Considerations

Additional points for consideration include:

- The granularity of any available historic scheduled flows – the detailed technical model definition will inform if this granularity is sufficient.
- The usability of historic market data, which is theoretically available though may require purchase. As noted above, just the final values would likely not provide sufficient levels of granularity for a given time period.

5.3.5 Regulatory Considerations, Explainable AI, and Process Impacts

As with the other modelling areas, implementation of such a final vision methodology raises points for consideration around explain-ability etc.

5.3.5.1 Trading Decisions

For interconnectors, any forecasted flows would have clear impacts on trading decisions and processes. A sufficient level of understanding and AI transparency would likely be required to justify the cost of said trading decisions.

However, the potential difficulties in developing an accurate model (see discussion point below) could result in a perceived "untrustworthiness" of the forecasted flows. In this case, even a thorough understanding of the underlying logic may not be adequate to defend resultant trading decisions.

5.3.6 Discussion Point: Is attempted forecasting of interconnector flow a worthwhile endeavour?

As noted above, the fast-shifting nature of interconnector flows, due in part to their close dependencies on market conditions, make them particularly difficult to accurately forecast. Whilst the overall dynamics of the system are relatively well understood, the difficulties arise in trying to accurately forecast the underlying market conditions.

The subsequent uncertainty associated with these forecasts therefore raises the question:

Is attempted forecasting of interconnector flow a worthwhile endeavour?

In other words, would "perfect" data and modelling methodology ever be able to capture the intricacies and volatile profile of interconnector flows to a useful level?

In answering this question thoroughly, one must consider:

- The incremental value add of improved forecasting,
- The balance between said incremental value and development / implementation costs – how accurate would forecasting have to be for this approach to be worthwhile?
- The upper limit of forecasting accuracy,
- Etc.

With feedback suggesting that current interconnector forecasts are widely speculative, significant improvements would be required to build a usable, useful asset.

5.3.7 Next Steps

The separately delivered "Roadmap" output will specify next steps in working towards the more holistic longer-term end vision.

However, as indicated above, there are a few immediate steps that can be taken to progress this area. These include:

1. Further detailed analysis of data sources (some requiring purchase) to establish whether granularity and quality are sufficient for this purpose – in particular, the timescales of "scheduled flows", and ability to forecast market data in the creation of scenarios.
2. Discussion around anticipated value and likely accuracy of this model given the relatively sporadic, rapidly shifting nature of interconnector flows (see discussion in section 5.3.6) – initial data science analysis could provide a view of likely accuracy limits.
3. Initial Data Science workstream activities (see 4.2.1).

5.4 Adaptive Distributed Energy Resource (DER) Models

5.4.1 Overview

The Adaptive Distributed Energy Resource (DER) Models described by Google X Tapestry in the output document Advanced Dispatch Optimizer System Roadmap Report are analogous to the generation models in structure. However, as the name suggests, the focus is on all visible DER resources participating in the market. Visibility to system operators is a crucial attribute, with embedded DERs that are not visible being handled within the Net Demand models. Note the term DER here may refer to individual resources or aggregated resources as required.

[Clarification from Google X suggests that grid scale duration limited assets, such as batteries and pumped storage, are included within the Adaptive Generation model group, whilst, for example, smaller instructible batteries connected at the distribution level and participating in the markets are considered as part of this section.]

The overall model purpose is "*to correct, enhance and create distributed energy resource input data*" for the optimiser module. This purpose translates into two primary outputs:

- Probabilistic scenario testing capability to forecast the likely response to given dispatch instructions,
- Correction / validation of held static data (e.g., Megawatt (MW) limits, ramp rates[32]).

The core functionality centres around the scenario testing capability, with the improvement of held static data being a useful secondary output. When viewed through a holistic architectural lens, the scenario-based approach provides consistency across the model types and enables coherent testing of output sensitivity to conditions (see Architecture deliverable). Further, whilst it is noted that market participants should generally be providing accurate technical parameters, this correction / validation will catch any discrepancies in performance.

The detail around this specification is given in the "Required Final Capability" section below, with particular focus on the scenario testing capability and associated options.

The DER model sections below aim to outline some of the current and planned DER forecast capabilities, detail the final vision (highlighting any decision points for consideration), and discuss some comparative gaps. [Note: The main As-Is analysis and gap analysis sit within a different deliverable but relevant data points are discussed here.]

5.4.2 Existing and Planned Capabilities

[See As-Is deliverable for full overview.]

Below is an overview of some relevant elements but, as noted above, the true As-Is analysis sits separately to this report, and as such the below is far from exhaustive.

[32] Given the nature of DERs, this data may not be static for some resources.

There is no current explicit ESO capability to forecast the output of aggregated DERs, or individual resources. The generation output of distribution level resources is currently forecasted at GSP and National levels using PEF and AMIRA.

As described previously:

5.4.2.1 EFS / PEF Generation Capability

The Energy Forecasting System (EFS), gradually being replaced in functionality by the Platform for Energy Forecasting (PEF), covers multiple areas.

At a high level, PEF focuses on four core products (not all relating to generation):

1. National demand forecast,
2. Wind power generation forecast,
3. Solar power (Photovoltaic; PV) generation forecast,
4. Grid supply point (GSP) forecast for demand, solar, and wind.

Machine Learning models are used for the GSP and PV generation products, and a similar model for wind generation is also under construction. Current approaches are generally deterministic (outputting a single, fixed solution per run) and provide a set of forecast variants (minimum, maximum and average). PEF feeds into BM-SPICE, which subsequently feeds into BM-SORT.

5.4.2.2 AMIRA

AMIRA is a third-party tool used by the control room to forecast metered wind generation and the associated error probabilities. None of the outputs feed into any other systems in the control room, with elements being manually typed over by the OEM. Feedback suggests that AMIRA provides a consistently more accurate forecast than PEF.

5.4.3 Required Final Capability

The required final capability discussed below interprets the description provided in Google X Tapestry's Advanced Dispatch Optimizer System Roadmap Report, providing a much greater level of detail, and highlighting arising decision points / considerations.

Tapestry notes that "*To our knowledge, no such adaptive DER modelling approach has been implemented by a Grid Operator*", thus emphasising the innovative nature of this element.

Each DER model aims to provide, for a given resource / aggregated resource group, a half-hourly[33] view of expected actual output (in MW) under a given set of hypothetical dispatch instructions. In other words, the model aims to answer the question:

[33] Half-hourly is the minimum temporal granularity required. Interpolating for shorter steps within the dispatch process would likely provide further beneficial insight.

Given a set of dispatch instructions to test, combined with forecast input data such as weather, likely maintenance etc., what is the predicted actual MW output for a specified resource / aggregated resource group?[34]

The below figure provides an initial high-level view of the required (supervised) model creation and scenario testing process.

[Note: The previously mentioned similarity to the Generation models is clear in the below sections, with certain considerations repeated verbatim.]

[34] Feedback suggests that a more appropriate question could focus on prediction of output before the instruction, as opposed to after (with units generally expected to deliver when instructed, and uncertainty arising from, for example, accuracy of PNs). Theoretically, this model type could answer both questions given the similar underlying data requirements, with the pre-instruction predicted output tested for relevant timeframes via a "blank" instruction.

5.4.3.1 Overview

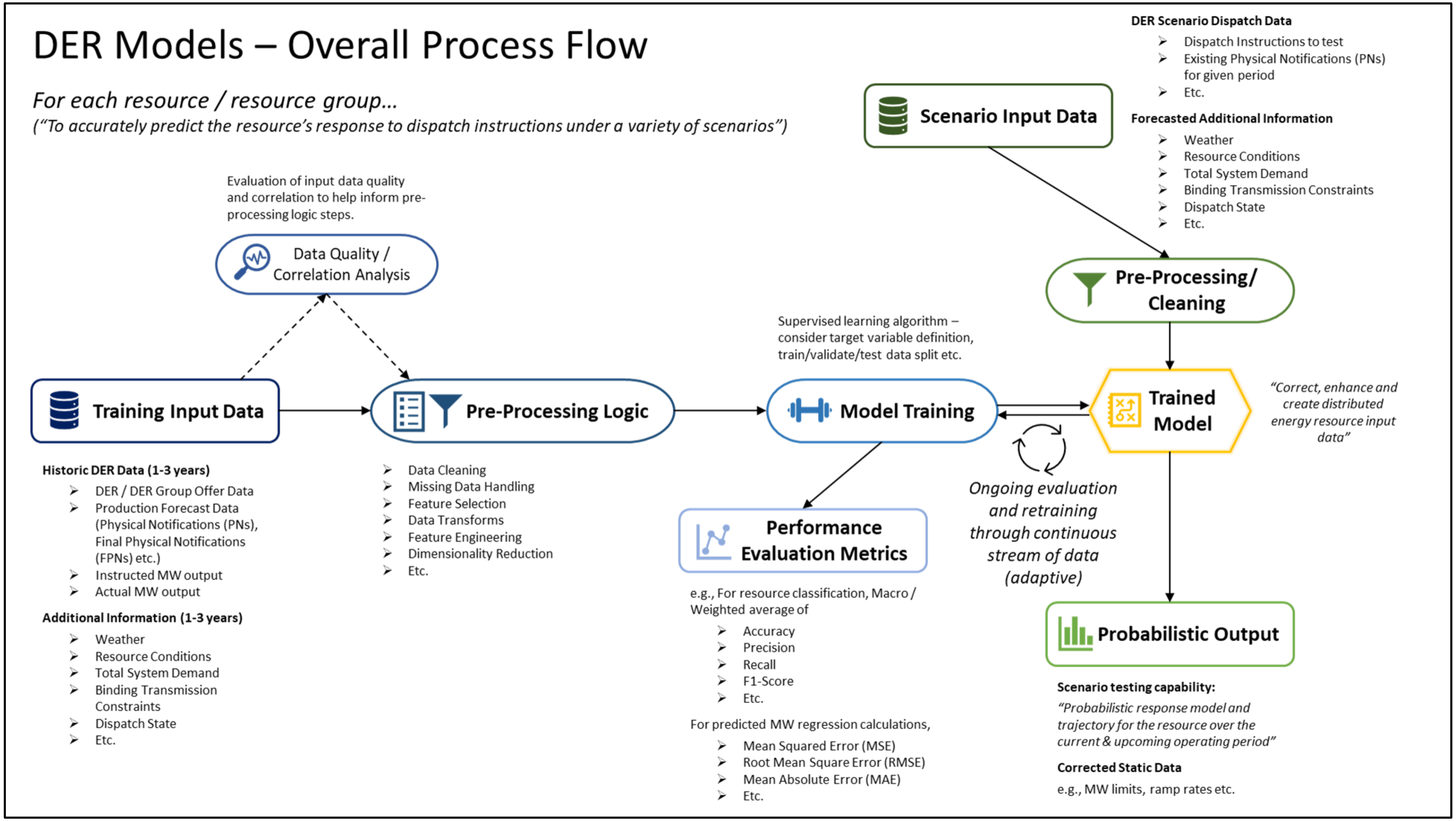

Figure 25: DER Models – Overall High-Level Process Flow

[Note: Feedback suggests that this outlined process is similar in principle to the PEF Machine Learning models, though their blended output is deterministic.]

For a brief description of these process stages, as previously, see section 5.1.3.1.

The model in question uses supervised learning techniques to predict the actual half-hourly MW output for a resource / aggregated resource group under given dispatch instructions.

Considerations around the form of the model output, as well as the final output from potentially running multiple scenario tests to account for uncertainty in the forecasted input variables, are discussed at length in sections “Modelling Approach Considerations” and “Scenario Testing Capability and Output”. These sections explore the possibilities of probabilistic base models (as opposed to point estimates) and probabilistic outputs from scenario testing[35].

5.4.3.2 Data Requirements Overview

Within the process flow shown, data requirements can broadly be split into two categories: Historic Training Data and Scenario Input Data. Potential data sources are discussed in the data availability section.

Historic Training Data

Training data refers to the set of historical (labelled) data that will be used to train the first iteration of the model. Said training data will later be updated over time in line with a defined re-training schedule.

The training data for these models consists of, for each DER / DER group in question, Historical DER Data (i.e., *What has happened previously with regards expected vs. actual outputs within the Balancing process?*) and Additional Information for correlation tests (i.e., *What external factors may account for any discrepancy observed in expected vs. actual output?*).

Table 28: DER Models – Training Data

Category	Data	Description	Frequency	Total Time
Historical DER Data	DER / DER Group Offer Data	Logged DER / DER group BOAs, Bid Offer Data (BOD), including increase / decrease limits and associated prices.	Half-hourly (for each dispatch interval)	At least 1 year (Tapestry minimum), preferably approx. 3 years (IBM view).
	Production Forecast Data	DER / DER group forecast output figures over time (including PNs, FPNs).	Half-hourly (for each dispatch interval)	
	Instructed MW output	Instructed MW output by DER / DER group over time.	Half-hourly (for each dispatch interval)	

[35] As noted previously, when viewed through a holistic architectural lens, the scenario-based approach provides consistency across the model types and enables coherent testing of output sensitivity to conditions (see Architecture deliverable).

	Actual MW output	Actual MW output by DER / DER group over time.	Half-hourly (for each dispatch interval)	
Additional Information	Weather	Weather data for each resource location (temperature, precipitation, UV levels, wind speed etc.).	Half-hourly profiles	
	Resource Conditions	Resource conditions over time, including maintenance activities (both planned and unexpected outages).	Ad-hoc	
	Total System Demand	Total system demand over time.	Half-hourly	
	Binding Transmission Constraints	All active constraints over time (both planned and unexpected).	Ad-hoc	
	Dispatch State	Dispatch state by resource over time (e.g., ramping up, holding etc.) – to understand, for example, ramp-up rates.	Ad-hoc	

As previously, there is a balance to be struck between model accuracy and data gathering complexity. It is important to remember that further re-training will be continuous as more data is collected, thus improving the accuracy of the model.

Scenario Input Data

Scenario Input Data here refers to the set of information fed into the trained model to produce the probabilistic output desired. What the model requires as input is a set of forecasted data covering all the previously defined "Additional Information" variables (forecasted for the given timeframe in question), as well as the particular dispatch scenario to be tested.

In other words, for the given future time in question, the model input data consists of, for each DER / DER group, Scenario Dispatch Data (i.e., *What set of dispatch lever options are we looking to understand the impact of?*) and Forecasted Additional Information (i.e., *How do we expect the factors affecting dispatch response to be behaving over the time in question?*).

Table 29: DER Models – Scenario Input Data

Category	Data	Description	Time
Scenario Dispatch Data	Theoretical Dispatch Instructions	Set of potential dispatch instructions to be tested in the model.	Given future time period in question.
	Existing PNs for given period	Existing DER / DER group PNs for the time period being considered.	

	DER / DER Group Offer Data	Available DER / DER group Bid Offer Data (BOD), including increase / decrease limits and associated prices. (Relevance dependent on when the model is being run relative to the period in question.)	
Forecasted Additional Information	Weather	Weather data for each generator location (temperature, precipitation, UV levels, wind speed).	
	Resource Conditions	Resource conditions over time, including maintenance activities (both planned and unexpected outages).	
	Total System Demand	Total system demand over time.	
	Binding Transmission Constraints	All active constraints.	
	Dispatch State	Dispatch state changes by resource over time (e.g., ramping up, holding etc.).	

[Note: Given the number of variables, the scenario definition process itself could exist as a separate problem. Management of this is briefly discussed in the below section "Scenario Testing Capability and Output", as well as within the Architecture deliverable.]

5.4.3.3 Data Models

The below logical entity-relationship diagrams provide a view of how both the scenario input data sources, and separately the training data sources, could relate and be structured.[36]

[36] See section 7 for overview of entity-relationship notation.

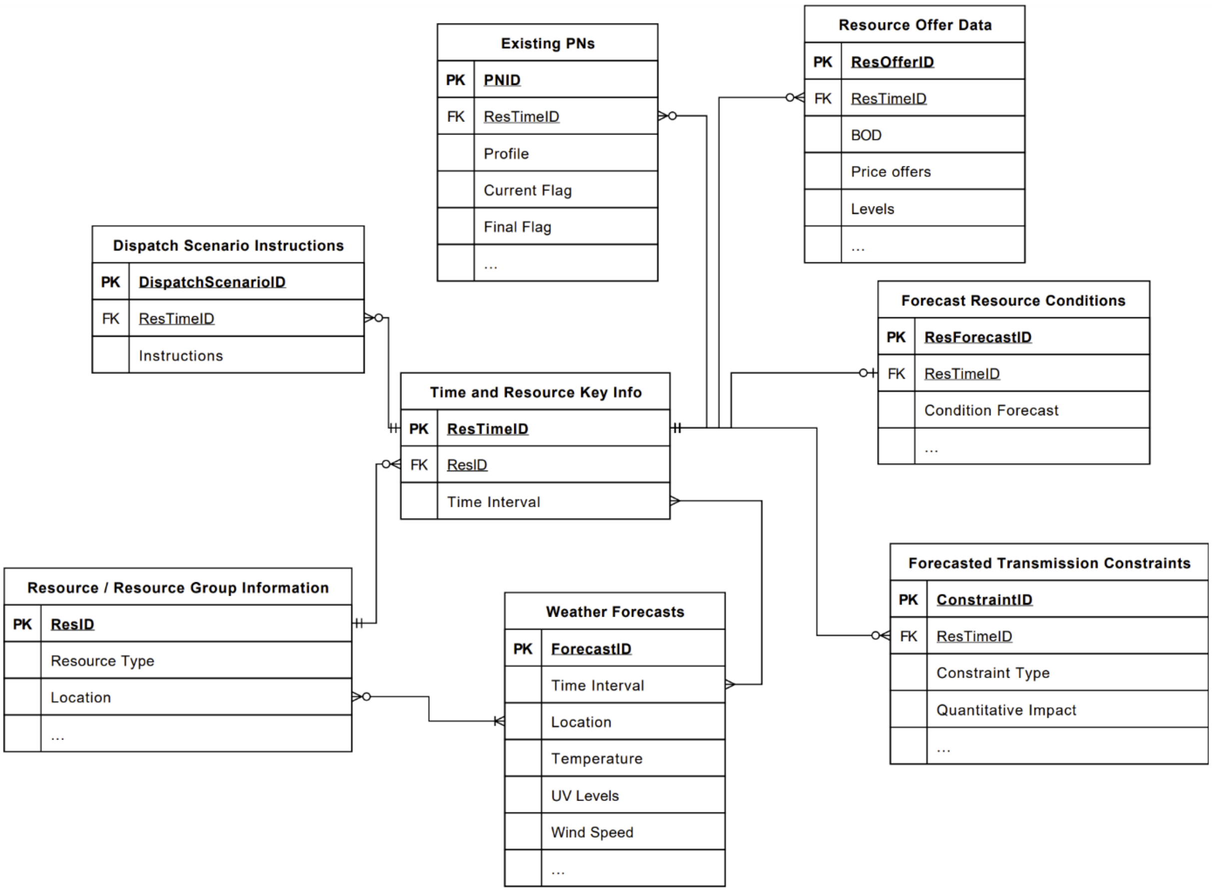

Figure 26: DER Models – Example view of data model for scenario input data sources

This model exemplifies the relationships between the different data sources and provides a practical view as to one way the end vision data structures could be realised.

As an example, the dispatch scenario instructions to test within the DER models are linked via a key to the specific resource / resource group ID and time interval being trialled. Shown by the connection types in the above diagram, each set of instructions will join to precisely one Resource / Time Interval combination key, whilst each such key may link to multiple trial instructions. The Resource ID can then be further used to gather information such as location (at required level of granularity) to link weather forecasts etc.

Similarly for the listed historic training data:

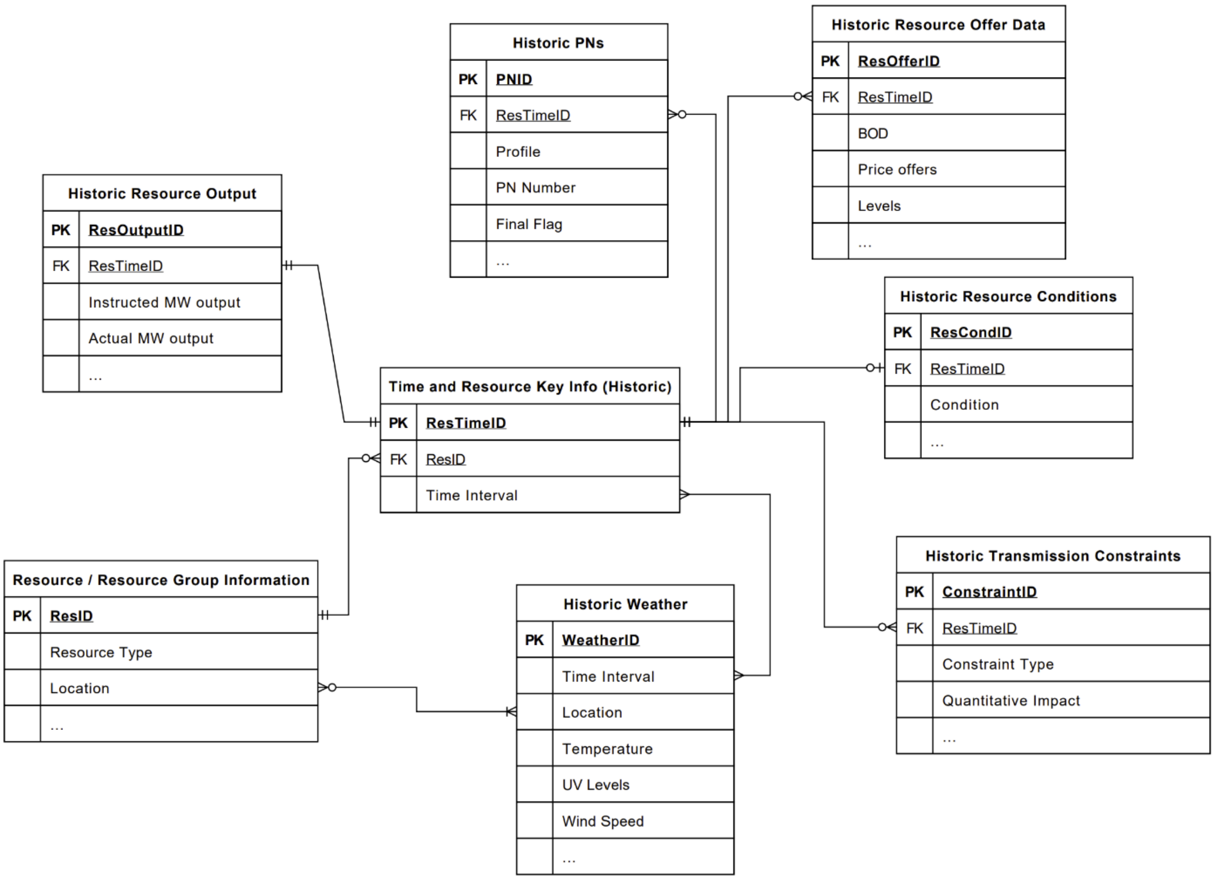

Figure 27: DER Models – Example view of data model for training data sources

5.4.3.4 Modelling Approach Considerations

Due to the almost identical problem structure and model type, the considerations outlined in the Generation Models section (Regression vs. Classification and Deterministic vs. Probabilistic) are also valid here. To avoid repetition, please refer to section 5.1.3.4 for definition and discussion of these points.

<u>Considerations for DER Input Data Models</u>

An equivalent algorithm matrix to that produced for Generation Models is shown below.

Deterministic Regression *Predicting a single numerical value for actual output for each half-hour interval, given a set of input conditions.*	**Deterministic Classification** *Predicting a single class (group) value for actual output for each half-hour interval, given a set of input conditions.*
Probabilistic Regression *Giving a probability distribution across numerical values for actual output for each half-hour interval, given a set of input conditions.*	**Probabilistic Classification** *Giving a probability distribution across class (group) values for actual output for each half-hour interval, given a set of input conditions.*

Figure 28: DER Models – Matrix of modelling techniques

5.4.3.5 Scenario Testing Capability and Output

As with the modelling approach, the considerations arising around running of the scenario testing capability (deterministic single run vs. deterministic multi-run vs. probabilistic single run etc.) are identical to those discussed in section 5.1.3.5. These are therefore not repeated in full here.

However, equivalent views of sample parameter spaces and distribution output from a deterministic multi-run approach are shown below.

Table 30: DER Models – Example parameter space for scenario testing

Category	Data Type	Parameter	e.g., Discrete Range	e.g., Distribution
Forecasted Additional Information	Weather	Temperature (°C)	[16, 17, ...]	$T \sim \mathrm{N}(18,4)$
		Wind speed (mph)	[10, 12, ...]	$v \sim \Gamma(15,1)$
		UV Index	[3, 4, ...]	$\vartheta \sim \Gamma(7.5,1)$
		Etc.		
	Resource Conditions	Active Maintenance Boolean	[0, 1]	$\kappa \sim Ber(0.1)$
		Etc.		
	Total System Demand	Total demand for given area (MW)	[500, 550, ...]	$\Delta \sim \mathrm{N}(650,70)$
	Etc.			

[Note: example discrete ranges and distributions are purely illustrative.]

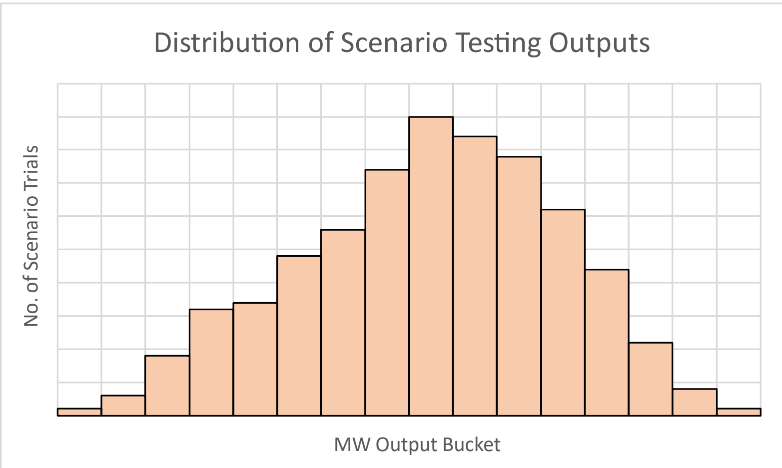

Figure 29: DER Models – Example distribution output from running multiple trials with a deterministic model

5.4.3.6 Further Considerations

As in section 5.1.3.6.

Additionally:

Distribution System Operator (DSO) Ownership

Put simply, should this detailed understanding of DERs be the responsibility of DSOs? Given the connection point of these resources is at the distribution level, one could argue that the DSOs are best placed to own this capability. If so, this has some implications regarding Explainable AI etc. (see discussion below).[37]

Further, there are other reasons why this information may be of use to the DSOs – for example, predicting reverse power flows. Factors like this could become the primary drivers towards DSO ownership.

Aggregation Concerns

As noted, this capability is intended to model the response of individual resources or aggregated resources as required. The arising issue concerns the definition of aggregated resources and how they are treated with respect to generated constraints.

Theoretically there is no current limit to the size of units that can be included as part of an aggregated resource. In addition, the individual units making up said aggregated resource could be geographically dispersed across multiple GSPs. Without full insight into the positions of the individual constituent units, one could "accidently" send instructions to a constrained area. This becomes particularly problematic if the instructed unit is large enough to noticeably impact the dispatch outcome[38].

Given this, an arising consideration is whether modelling of aggregated resources is sufficiently granular, or if more data is required on the individual constituent units.

[Note: Discussions with the regulator regarding these issues are included as part of the roadmap deliverable.]

5.4.4 Data Gap Analysis

As is to be expected when defining a new, innovative capability, none of the existing or planned processes completely meet the requirements outlined in "Required Final Capability". However, mapping said requirements to existing data sources and techniques provides a clearer view of missing elements, as well as next steps.

As noted previously, the true gap analysis deliverable sits separately to this report, and the below section therefore comments only on data availability and quality.

[37] A potential area to explore is the DER visibility innovation project.
[38] Feedback suggests this is a rare occurrence currently due to the relatively small size of the individual units making up aggregated resources. However, as the market continues to grow, the lack of a unit size restriction may alter behaviour.

5.4.4.1 Overview

Similar to the generation models, there are different forecasting and optimisation tools currently in use. The novelty here, again, lies in the prediction of discrepancy between FPNs altered by BOAs and actual output.

5.4.4.2 Availability of Data

The below tables provide an overview of the currently understood data availability gap. Note the parallels to the availability of generation model data.

<u>Historic Training Data</u>

There is a hope that some of this historic data may exist in yet unexplored data silos. However, the working theory from SMEs is that ***approx. 3 years of data collection in real time would be required in order to meet the historic "Additional Information" data requirements outlined[39].***

Table 31: DER Models – Training Data Availability

Category	Data	Frequency Required	Total Time	Currently Understood Availability
Historical DER Data	DER / DER Group Offer Data	Half-hourly (for each dispatch interval)	At least 1 year (Tapestry minimum), preferably approx. 3 years (IBM view).	Available, stored in National Grid Economic Database, NED (from the start of New Electricity Trading Arrangements (NETA) in 2001).
	Production Forecast Data	Half-hourly (for each dispatch interval)		Available, stored in NED (from the start of NETA in 2001).
	Instructed MW output	Half-hourly (for each dispatch interval)		Available, stored in NED (from the start of NETA in 2001).
	Actual MW output	Half-hourly (for each dispatch interval)		Available, stored in Data Historian.
Additional Information	Weather	Half-hourly profiles		Some wind related data available (wind speed vs. wind power), stored in NED – unsure of exact storage length. Alternatively available through MET Office Weather Data for Business (wind,

[39] It is worth noting that the full data requirements listed may not be necessary for a first model iteration. Analysis of model performance over time will indicate whether the currently unavailable variables will significantly improve forecast accuracy.

				temperature, radiation levels etc.).
	Resource Conditions	Ad-hoc		Not aware of existence. *Perhaps resources hold this historic data?*
	Total System Demand	Half-hourly		Demand profiles kept for selected days (e.g., Coronations). Not aware of more extensive records.
	Binding Transmission Constraints	Ad-hoc		Not aware of any archiving of constraints.
	Dispatch State	Ad-hoc		Unclear – can perhaps be deduced but may not be required.

Scenario Input Data

Availability of the Scenario Input Data "Additional" variables is inherently related to the above availability of Training Data. The difference arises in the time horizon being considered, with Training Data being historical and Scenario Input Data being forward-looking.

Data groups required for scenario testing are generally more available, and hence not as restrictive to model development as the above training data.

Table 32: DER Models – Input Data Availability

Category	Data	Time	Currently Understood Availability
Scenario Dispatch Data	Theoretical Dispatch Instructions	Given future time period in question.	To be created as part of model input.
	Existing PNs for given period		Received by ESO and available. [Quantity dependent on time horizon of future time period in question.]
	DER / DER Group Offer Data		Received by ESO and available. [Quantity dependent on time horizon of future time period in question.]
Forecasted Additional Information	Weather		Forecast data available and utilised.
	Resource Conditions		Dependent on time horizons – not aware of longer-term planning from all individual resources.
	Total System Demand		Forecast data available and utilised.
	Binding Transmission Constraints		Forecast data available and utilised. [When considering short time horizons, active transmission

			constraints can be obtained from the Adaptive Transmission Model.]
	Dispatch State		Current dispatch states, requirement for "warming" etc. understood.

[Note: The type and availability of this data stems from the fact that this model is specifically considering visible DERs participating in the market. Embedded DERs will, by definition, not have the same level of available data.]

5.4.4.3 Data Quality / Granularity Analysis

As expected, due to the similar underlying data sources, data quality and granularity comments noted in section 5.1.4.3 are also applicable here.

5.4.5 Regulatory Considerations, Explainable AI, and Process Impacts

As with other areas, there are again various points for consideration around explain-ability, impact on existing processes etc.

5.4.5.1 DSO Ownership

In the case of the potential DSO ownership model discussed above, the required DER data would sit outside of ESO's responsibility. In order to cover the full landscape of *Explainable AI* considerations, there requires a level of transparency around the input data and processes involved in producing the desired output. This likely requires a contractual change to the ESO relationship with the DSOs, ensuring that this level of transparency is achieved.

5.4.5.2 Aggregation Concerns

As explained above, there are concerns around the treatment of aggregated resources, and the potential "accidental" instruction of dispatch in a constrained area. *Explainable AI* considerations in this area cover the understandability of output and subsequent action. If the data is of insufficient granularity to reach the level of clarity required, the model arguably falls short of explain-ability conditions.

5.4.6 Next Steps

The separately delivered "Roadmap" output will specify next steps in working towards the more holistic longer-term end vision.

However, as indicated above, there are a few immediate steps that can be taken to progress this area. These include:

1. Discussion with DSOs regarding the ownership of models relating to distribution network-connected assets.

2. Addressing of data availability issues by planning for a multi-year data collection period where necessary for model training purposes.
3. Initial Data Science workstream activities (see 4.2.1).

6 Advanced Net Demand Forecast Module

The Google X Tapestry report provides a brief description of a proposed Adaptive Net Demand Forecast Module. The overall quoted purpose of this module is to "*create forecasts, probabilistic trajectories, and scenarios for Net Demand at a substation, regional and total market level*". This is to be achieved by utilising the synergy between two individual components:

1. Demand Forecast and Consumer Behaviour,
2. Embedded DER.

These component models are explored separately below, though would work in combination to achieve the overarching goal above.

Tapestry notes that "*To our knowledge, no such adaptive net demand modelling approach has been implemented by a Grid Operator*", thus emphasising the innovative nature of this module as a whole.

With the net demand module description presented by Google X sitting at a very high level, several considerations are highlighted below when detailing this area.

6.1 Discussion Point: Should modelling of net demand be split as indicated into actual demand and embedded DER modules?

As described above, Tapestry's report explicitly splits net demand modelling into two constituent modules. These modules model actual demand and, separately, impact of embedded DERs, with a view of combining these in a simple calculation to obtain net demand at the given level of granularity. Net demand is the important measure for ESO, with the underlying modelling of actual demand and embedded DERs seemingly just a means to an end (trying to improve the accuracy of net demand forecasts by modelling the nuances of the fast-moving embedded DER market, rather than treating it as an "opaque box").

Given smart meter data reflects net demand directly and this could theoretically be used to extrapolate to a given geographical granularity, questions arising include:

At what level should net demand be modelled? Is it worth splitting into actual demand and embedded DER modules? Does this greatly impact net demand forecast accuracy? Instead, is it sufficient to directly model net demand? Is there an additional benefit to understanding presence and utilisation of embedded DERs (over and above the modelling of net demand)?

The answers to these questions dictate the overall approach to be taken in this area. The "clear" modelling (splitting into individually modelled components) would require a good understanding of the internal system structure and dynamics, whereas the "opaque" net modelling approach would have a greater reliance on large volumes of good quality training data.

Whilst the separated actual demand and embedded DER components (as defined by Tapestry) are explored below, a single net demand model may be preferrable in reality.

6.2 Discussion Point: With whom should the responsibility of providing accurate demand forecasts sit?

As seen with other modelling areas, there often arises a question as to whether ESO should hold the responsibility of creating accurate forecast data. In the case of demand modelling, should this capability instead sit with other parties such as suppliers or aggregators? The roadmap deliverable addresses this point by incorporating an analysis of the incentive, impact, value, and feasibility of other parties owning this element.

6.3 Adaptive Demand Forecast and Consumer Behaviour Model

6.3.1 Overview

As noted above, the overarching purpose of the demand module is to "*create forecasts, probabilistic trajectories, and scenarios for Net Demand at a substation, regional and total market level*". Specifically for the Adaptive Demand Forecast and Consumer Behaviour model element, the goal is to forecast actual demand[40] under a given set of conditions. Analogous to other model groups, this translates to an output of:

- Probabilistic scenario testing capability to forecast the likely actual demand under given conditions.

When viewed through a holistic architectural lens, the scenario-based approach provides consistency across the model types and enables coherent testing of output sensitivity to conditions (see Architecture deliverable).

The demand forecast and consumer behaviour model sections below aim to outline some of the current and planned demand forecast capabilities, detail the final vision (highlighting any decision points for consideration), and discuss some comparative gaps. [Note: The main As-Is analysis and gap analysis sit within a different deliverable but relevant data points are discussed here.]

6.3.2 Existing and Planned Capabilities

[See As-Is deliverable for full overview.]

Whilst there is no current capability to forecast demand at the consumer level, there are several existing tools used to look at the GSP level of spatial granularity. Below is an overview of some relevant elements but, as noted above, the true As-Is analysis sits separately to this report, and as such the below is far from exhaustive.

The ESO control room utilises three tools to forecast demand:

- Platform for Energy Forecasting (PEF),
- Real-Time Predictor (also referred to as "Demand Predictor"),
- AMIRA.

[40] Actual Demand = Net Demand – Embedded DER Activity

Further, as detailed below, there is an ongoing innovation project known as "CrowdFlex" which would provide a half-hourly unit-level forecast of demand.

6.3.2.1 EFS / PEF Demand Capability

The Energy Forecasting System (EFS), gradually being replaced in functionality by the Platform for Energy Forecasting (PEF), covers multiple areas.

At a high level, PEF focuses on four core products (not all relating to demand):

1. National demand forecast,
2. Wind power generation forecast,
3. Solar power (Photovoltaic; PV) generation forecast,
4. Grid supply point (GSP) forecast for demand, solar, and wind.

Specifically for demand, we have two key outputs:

- *National Demand* = the sum of generation leaving the transmission system, including metered and embedded generation
- *GSP Net Demand* = net Super Grid Transform (SGT) load that is balanced at all points in time.

Both National Demand and GSP Net Demand are forecast using deterministic models, with the PEF roadmap planning a shift towards probabilistic modelling.

6.3.2.2 Real-Time Predictor

Real-Time Predictor is used to "fix" the forecast data produced by other tools, providing a more granular minute-by-minute forecasting solution. This is achieved by taking real-time data inputs from iEMS (shifting to NCMS), the forecast output from PEF, and the profile of the closest matching historic day (as judged by the OEM). Bending of the historic curve to match cardinal points, Real-Time Predictor uses a regression algorithm to predict minute-by-minute demand.

6.3.2.3 AMIRA

As mentioned in previous sections of this report, AMIRA is a third-party tool used by the control room to forecast demand and the associated error probability. The outputs of this tool do not feed directly into any other systems in the control room, with certain elements typed across manually by the OEM.

6.3.2.4 CrowdFlex

Domestic flexibility is, by definition, stochastic due to its reliance on human behaviour. The CrowdFlex project aims to understand and utilise this fact to demonstrate how domestic flexibility can be a "*reliable energy and grid management resource*" at scale.

The CrowdFlex: Alpha Model Specification document[41] outlines in detail the requirement for two distinct model types in trying to better understand the probabilistic nature of domestic demand. The following are proposed:

- Deterministic (simple linear regression) household-level Baseline Demand Model
- Probabilistic (simple quantile linear regression) aggregated GSP-level Flexibility Forecast Model

Whilst the exact model ownership structure is yet to be agreed (see figure below), creation of these models will provide ESO with a detailed view of forecasted demand, incorporating the additional complexity of flexibility events.

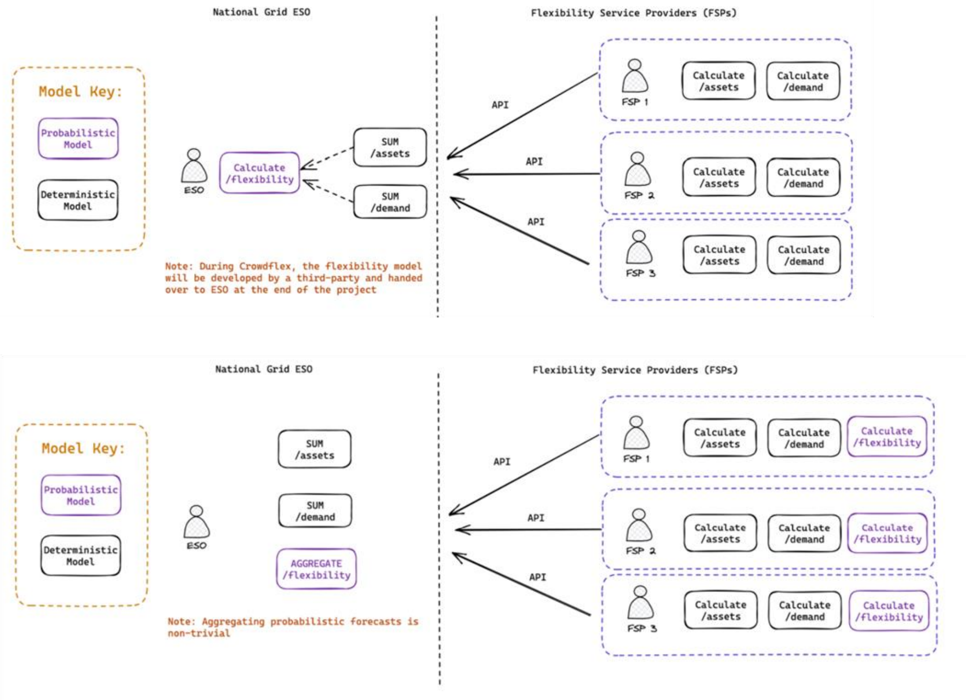

Figure 30: Model Ownership Options - D8.2 Model Specification and Delivery Plan

<u>Baseline Demand Model</u>

The underlying Baseline Demand Model is a household (unit)-level forecast of half-hourly electricity consumption. This model has 2 core use cases:

1. To provide ESO (as well as Flexibility Service Providers (FSPs) and potentially DSOs) with a clear view of forecasted domestic demand over a given period.
   [Note: the project scope is currently limited to forecasting those assets participating in the flexibility service, but the approach could be extended to all devices providing data feeds ("smart meter" MPANs and asset-level meters), and all domestic demand could therefore potentially be extrapolated.]
2. To help with settlement through consistent baselining approaches – both ESO / DSO to FSPs (at portfolio level relative to the baseline) and FSPs to consumers (at unit level relative to the baseline).

[41] D8.2 – Model Specification and Delivery Plan, January 2023

The model of choice for calculating the forecasted baseline demand is a simple linear regression. [Note: the rationale behind this choice is clearly outlined in the CrowdFlex: Alpha Model Specification document and as such is omitted here.] This model is described as "deterministic", meaning that it will produce a "single value" output (e.g., a single demand prediction for each half-hour interval) whilst also always producing the same output for a given set of inputs.

The required data inputs for this regression are specified as:

- "Lagged consumption features (from previous days, and weeks, up to 1 month ago)"
- "Forecasted weather features",

excluding previous flexibility event days so that the baseline is not skewed.

The output of this model, which will crucially be used as an input in the probabilistic flexibility model, will take the form of a half-hourly unit-level forecast of electricity consumption. Deterministic outputs such as this can then be readily aggregated to the desired level.

The frequency of model output update is suggested to vary depending on the nature of the consumption data. For energy suppliers, daily updates would be expected in line with receipt of updated smart meter data, whilst asset operators may be able to update more frequently due to the near real-time data stream from EVs or heat pumps.

<u>Flexibility Model</u>

The Flexibility Model takes the output of the FSP's Baseline Demand Models, aggregates them, and calculates the potential half-hourly domestic flexibility outturn of the specified set of assets (at GSP Group-level is proposed) in response to a particular flexibility event. The core purpose of this model is:

1. To enable users to evaluate the viability of using a proposed flexibility event as a lever to balance the grid (on both planning / scheduling and near real-time timescales).

The proposed model type for calculating this probabilistic flexibility outturn is a simple quantile linear regression model. [Note: Again, the rationale behind this choice is detailed in the CrowdFlex: Alpha Model Specification document.] In contrast to the above demand model, this model is described as "probabilistic". In practice, this means that the model incorporates randomness to produce a distribution of outputs.

The required data inputs are specified as:

- "Baseline demand forecast" aggregated to desired level (GSP Group is proposed)
- "Specification of the flexibility event intended to be run" (e.g., notice period, incentive level, duration, start time, event type, location, calendar variables etc.)
- "Weather inputs" (with acknowledgement that weather impacts the baseline input, but proposing experimentation to observe how it further impacts uptake of flexibility events)

In the use case envisaged in the design document, the model will return a probability distribution in the form of percentiles for the "updated demand distribution" at half-hourly intervals (accounting for the flexibility event).

<u>Initial Observations</u>

- Training of the Baseline Demand Model will require historic weather and consumption data for each unit (with weather data likely disaggregated to the required half-hourly frequency).
- The required quantity of this historic training data, whilst arguably subjective, should realistically cover at least 1 year (preferably more).
- For the Flexibility Model, training data will need to cover a sufficiently wide area of the flexibility event parameter space (notice period, incentive level, duration, start time, event type, etc.) as well as the corresponding event responses.
- The potentially variable level of aggregation performed could enable this demand modelling to feed into multiple other areas.
- If the population of households / assets within the CrowdFlex trial pool is not representative of the wider population, more work may be required before this type of model can be scaled. The study is designed and scaled to provide this representative sample, but this is a key project risk.

6.3.3 Required Final Capability

The required final capability discussed below interprets the description provided in Google X Tapestry's Advanced Dispatch Optimizer System Roadmap Report, providing a much greater level of detail, and highlighting arising decision points / considerations.

This adaptive demand forecast and consumer behaviour component aims to evaluate demand forecast performance – comparing actual demand[42] to historic forecasts to understand the impact of certain scenario conditions.

From this analysis, forecasts can be improved and run through a scenario testing capability. In other words, the model aims to answer the question:

Given a set of fixed inputs (e.g., day of week, time of day etc.), combined with forecast input data such as weather, market prices etc., and the existing demand forecast, what is the predicted actual demand at the chosen level of granularity?

The below figure provides an initial high-level view of the required (supervised) model creation and scenario testing process.

[42] Actual Demand = Net Demand – Embedded DER Activity

6.3.3.1 Overview

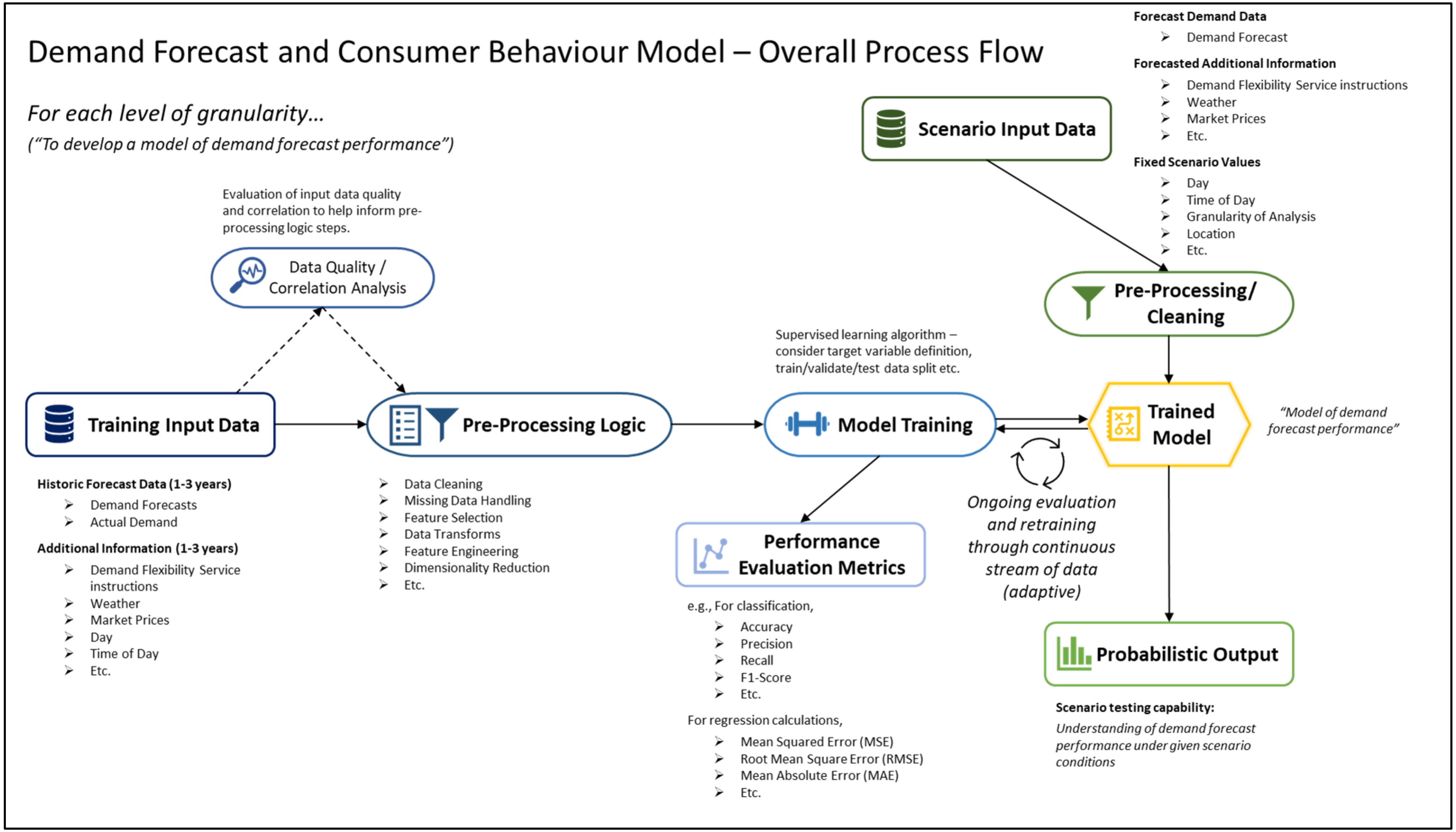

Figure 31: Demand Forecast and Consumer Behaviour Model – Overall High-Level Process Flo

For a brief description of these process stages, as previously, see section 5.1.3.1.

The model in question uses supervised learning techniques to predict the actual demand at the chosen level of granularity under a given set of scenario conditions.

Considerations around the form of the model output, as well as the final output from potentially running multiple scenario tests to account for uncertainty in the forecasted input variables, are discussed at length in sections "Modelling Approach Considerations" and "Scenario Testing Capability and Output". These sections explore the possibilities of probabilistic base models (as opposed to point estimates) and probabilistic outputs from scenario testing[43].

6.3.3.2 Data Requirements Overview

Within the process flow shown, data requirements can broadly be split into two categories: Historic Training Data and Scenario Input Data. Potential data sources are discussed in the data availability section.

<u>Historic Training Data</u>

Training data refers to the set of historical (labelled) data that will be used to train the first iteration of the model. Said training data will later be updated over time in line with a defined re-training schedule.

The training data for these models consists of, for each desired level of granularity, Historical Forecast Data (i.e., *What has happened previously with regards expected vs. actual demand?*) and Additional Information for correlation tests (i.e., *What external factors may account for any discrepancy observed in expected vs. actual demand?*).

Table 33: Demand Forecast and Consumer Behaviour Model – Training Data

Category	Data	Description	Frequency	Total Time
Historic Forecast Data	Demand Forecasts	Historic demand forecasts across a variety of leading timeframes.	Half-hourly (for each dispatch interval)	At least 1 year (Tapestry minimum), preferably approx. 3 years (IBM view).
	Actual Demand	Measured actual demand figures.	Half-hourly (for each dispatch interval)	
Additional Information	Demand Flexibility Service instructions	Flexibility service instructions – accounting for the reduction in actual demand exhibited by those instructed.	Half-hourly (for each dispatch interval)	
	Weather	Weather data for each relevant location at required lowest granularity level	Half-hourly profiles	

[43] As noted previously, when viewed through a holistic architectural lens, the scenario-based approach provides consistency across the model types and enables coherent testing of output sensitivity to conditions (see Architecture deliverable).

		(temperature, precipitation, UV levels, wind speed etc.).		
	Market Prices	Associated market prices for the half-hourly intervals.	Half-hourly (for each dispatch interval)	
Fixed Input Values	Day / Season	Date of historic data – accounting for elements such as demand seasonality, weekday vs. weekend behaviour change etc.	Fixed value for given actual demand	
	Time of Day	Time of historic data – accounting for daily patterns.	Fixed value for given actual demand	

As previously, there is a balance to be struck between model accuracy and data gathering complexity. It is important to remember that further re-training will be continuous as more data is collected, thus improving the accuracy of the model.

Scenario Input Data

Scenario Input Data here refers to the set of information fed into the trained model to produce the probabilistic output desired. What the model requires as input is a set of forecasted data covering all the previously defined "Additional Information" variables (forecasted for the given timeframe in question), as well as the existing demand forecast and associated fixed scenario values to be tested.

In other words, for the given future time in question, the model input data consists of Forecast Demand Data (i.e., *What forecast are we looking to understand the likely performance of?*), Fixed Scenario Values (i.e., *What type of scenario is being evaluated?*) and Forecasted Additional Information (i.e., *How do we expect the factors affecting demand forecast performance to be behaving over the time in question?*).

Table 34: Demand Forecast and Consumer Behaviour Model – Scenario Input Data

Category	Data	Description	Time
Forecasted Demand Data	Demand Forecasts	Forward looking demand forecast for time period in question.	Given future time period in question.
Forecasted Additional Information	Demand Flexibility Service instructions	Forecast of flexibility service instructions – accounting for the reduction in actual demand exhibited by those instructed.	
	Weather	Weather forecast data for each relevant location at required lowest granularity level (temperature, precipitation, UV levels, wind speed etc.).	

	Market Prices	Forecast market prices for time period in question.	
Fixed Scenario Values	Day / Season	Date of scenario – accounting for elements such as demand seasonality, weekday vs. weekend behaviour change etc.	
	Time of Day	Time of scenario – accounting for daily patterns.	

6.3.3.3 Data Models

The below logical entity-relationship diagrams provide a view of how both the scenario input data sources, and separately the training data sources, could relate and be structured.[44]

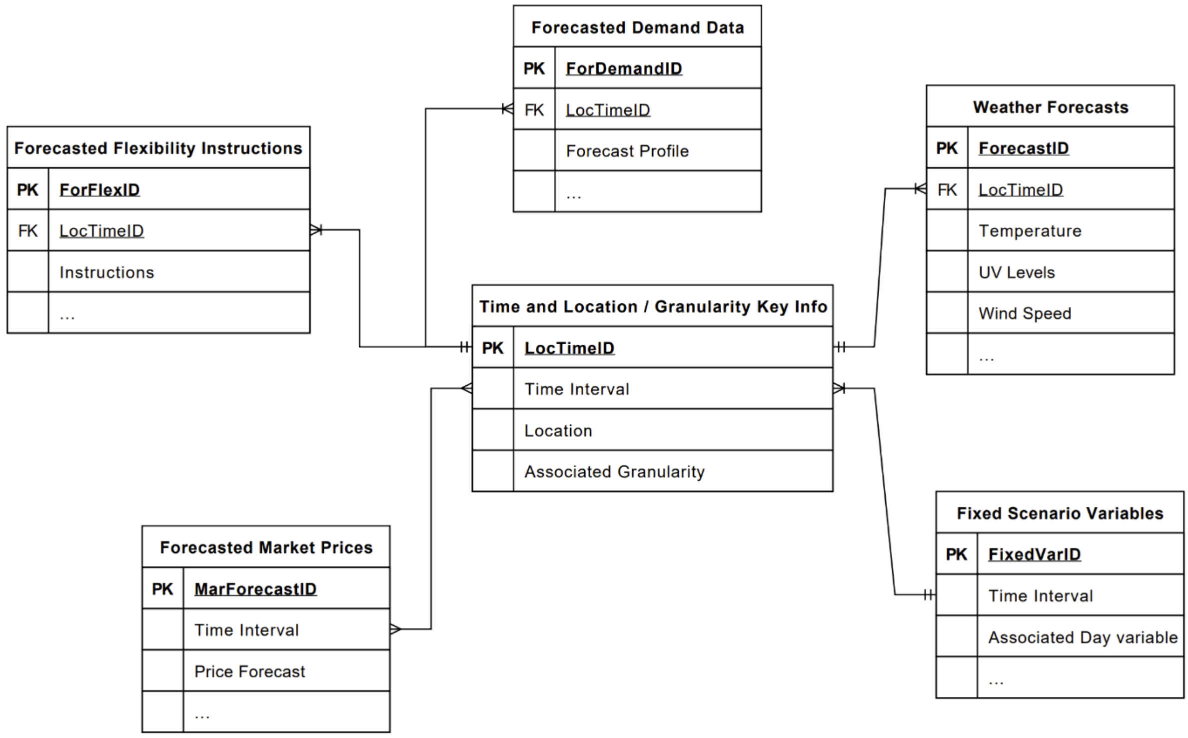

Figure 32: Demand Forecast and Consumer Behaviour Model – Example view of data model for scenario input data sources

This model exemplifies the relationships between the different data sources and provides a practical view as to one way the end vision data structures could be realised.

As an example, the forecasted demand profile to test within the performance evaluation model is linked via a key to the specific location (based on level of granularity – e.g., substation, regional etc.) and time interval being trialled. Shown by the connection types in the above diagram, each forecasted profile will join to precisely one Location / Time Interval combination key, whilst each such key may link to multiple demand forecasts. The Time

44 See section 7 for overview of entity-relationship notation.

Interval can then be further used to gather information such as forecasted market prices etc.

Similarly for the listed historic training data:

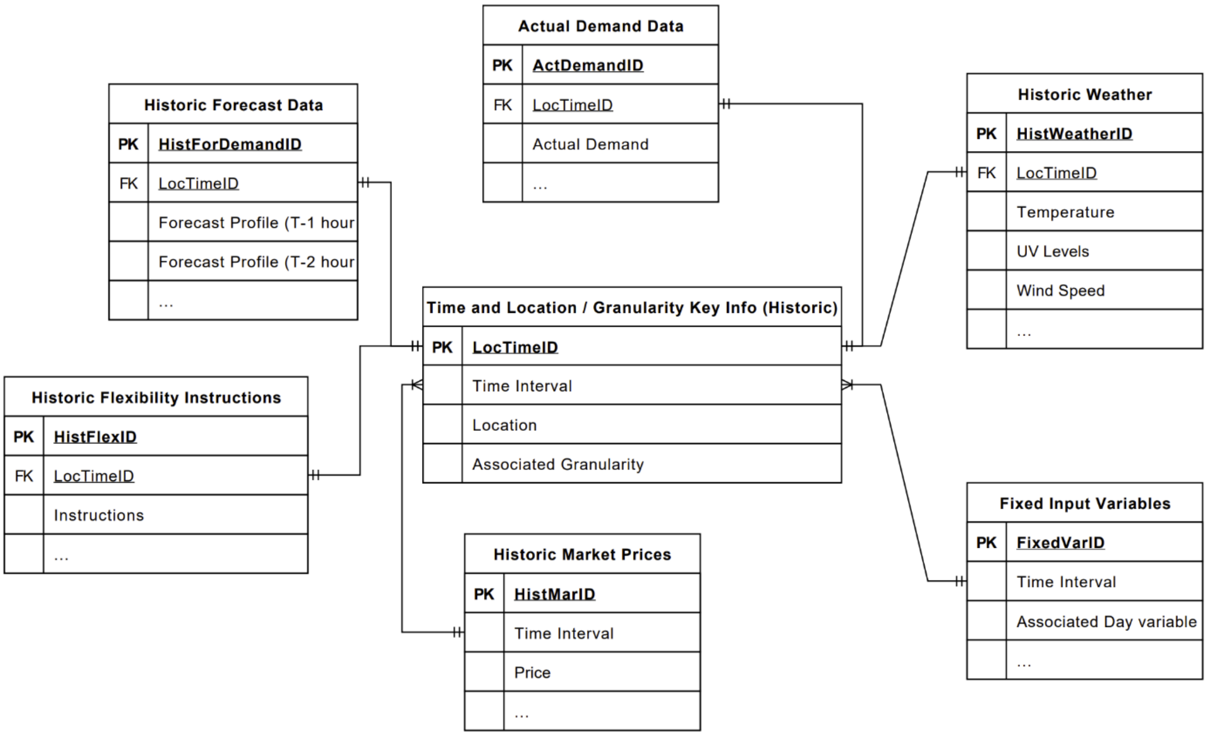

Figure 33: Demand Forecast and Consumer Behaviour Model – Example view of data model for training data sources

6.3.3.4 Modelling Approach Considerations

Due to the similar problem structure and model type, the considerations outlined in the Generation Models section (Regression vs. Classification and Deterministic vs. Probabilistic) are also valid here. To avoid repetition, please refer to section 5.1.3.4 for definition and discussion of these points.

Considerations for Demand Forecast and Consumer Behaviour Input Data Models

An equivalent algorithm matrix to that produced for Generation Models is shown below.

Deterministic Regression	**Deterministic Classification**
Predicting a single numerical value for actual demand for each half-hour interval, given a set of input conditions.	*Predicting a single class (group) value for actual demand for each half-hour interval, given a set of input conditions.*
Probabilistic Regression	**Probabilistic Classification**
Giving a probability distribution across numerical values for actual demand for each half-hour interval, given a set of input conditions.	*Giving a probability distribution across class (group) values for actual demand for each half-hour interval, given a set of input conditions.*

Figure 34: Demand Forecast and Consumer Behaviour Model – Matrix of modelling techniques

Additionally:

Impact of COVID19 Pandemic on Training Data

An important consideration, particularly for demand modelling, is the impact that the COVID19 pandemic had on consumer behaviour and, consequently, historic training data. The implementation of nationwide lockdowns to stem the spread of the virus greatly altered consumer daily demand profiles (with a sudden shift to increased working from home etc.). As a result, much of the recent historic demand data that would be used for model training purposes reflects this specific, isolated period of time which is no longer representative of customer behaviour.

Further, one must consider how current demand differs from pre-COVID19 profiles. For example, anecdotally, more individuals are making use of flexible working and work-from-home options. It could therefore be argued that longer-term changes to behaviour following the pandemic have resulted in a new landscape that is not accurately reflected by any previous data (pre or during pandemic). The nature of an adaptive model would hopefully quickly understand any discrepancy through continuous learning.[45]

6.3.3.5 Scenario Testing Capability and Output

As with the modelling approach, the considerations arising around running of the scenario testing capability (deterministic single run vs. deterministic multi-run vs. probabilistic single run etc.) are identical to those discussed in section 5.1.3.5. These are therefore not repeated in full here.

However, equivalent views of sample parameter spaces and distribution output from a deterministic multi-run approach are shown below.

[45] This is particularly relevant in the context of a rapidly changing global environment, with increased weather event frequency and severity, potential future pandemics etc.

Table 35: Demand Forecast and Consumer Behaviour Model – Example parameter space for scenario testing

Category	Data Type	Parameter	e.g., Discrete Range	e.g., Distribution
Forecasted Additional Information	Demand Flexibility Service instructions	Forecasted flexibility service instructions – e.g., taking the form of a (start time, end time, location, instruction) set of values	N/A	N/A
	Weather	Temperature (°C)	[16, 17, …]	$T \sim \mathrm{N}(18,4)$
		Wind speed (mph)	[10, 12, …]	$v \sim \Gamma(15,1)$
		UV Index	[3, 4, …]	$\vartheta \sim \Gamma(7.5,1)$
		Etc.		
	Market Prices	Forecasted energy cost profile – likely taking the form of a series of (time, £/MWh value) pairs	For the given time unit, [1.00, 1.15, …]	For the given time unit, $\vartheta \sim \Gamma(2,1)$
		Etc.		
	Etc.			

[Note: example discrete ranges and distributions are purely illustrative.]

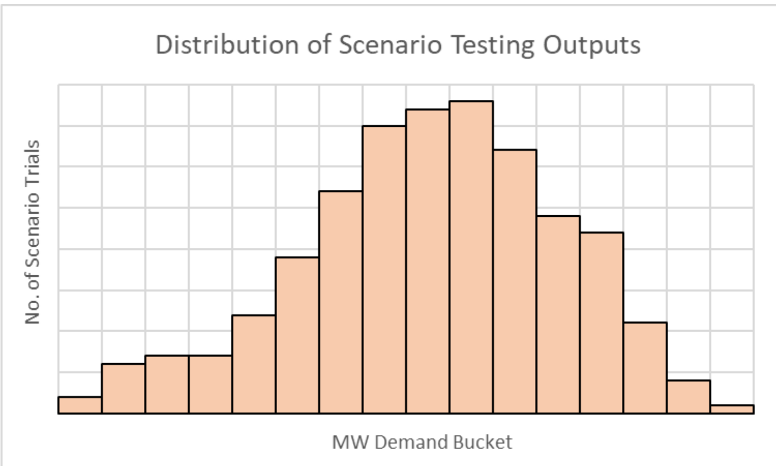

Figure 35: Demand Forecast and Consumer Behaviour Model – Example distribution output from running multiple trials with a deterministic model

6.3.4 Data Gap Analysis

As is to be expected when defining a new, innovative capability, none of the existing or planned processes completely meet the requirements outlined in "Required Final Capability". However, mapping said requirements to existing data sources and techniques provides a clearer view of missing elements, as well as next steps.

As noted previously, the true gap analysis deliverable sits separately to this report, and the below section therefore comments only on data availability and quality.

6.3.4.1 Overview

Demand is currently commonly defined as simply the sum of generation, with approximate constant frequency ensuring that generation and demand match. Feedback suggests that demand is therefore not technically forecasted in the way suggested here (independently of generation).

6.3.4.2 Availability of Data

The below tables provide an overview of the currently understood data availability gap.

We were unfortunately unable to obtain ESO SME input in this area within the required timeframe. As a result, the below sections are incomplete.

<u>Historic Training Data</u>

Table 36: Demand Forecast and Consumer Behaviour Model – Training Data Availability

Category	Data	Frequency	Total Time	Currently Understood Availability
Historic Forecast Data	Demand Forecasts	Half-hourly (for each dispatch interval)	At least 1 year (Tapestry minimum), preferably approx. 3 years (IBM view).	[Awaiting SME input.]
	Actual Demand	Half-hourly (for each dispatch interval)		[Awaiting SME input.]
Additional Information	Demand Flexibility Service instructions	Half-hourly (for each dispatch interval)		[Awaiting SME input.]
	Weather	Half-hourly profiles		Some wind related data available (wind speed vs. wind power), stored in NED – unsure of exact storage length. Alternatively available through MET Office Weather Data for Business (wind,

				temperature, radiation levels etc.).
	Market Prices[46]	Half-hourly (for each dispatch interval)		[Awaiting SME input.]
Fixed Input Values	Day / Season	Fixed value for given actual demand		Fixed value – determined by other inputs.
	Time of Day	Fixed value for given actual demand		Fixed value – determined by other inputs.

Scenario Input Data

Table 37: Demand Forecast and Consumer Behaviour Model – Input Data Availability

Category	Data	Time	Currently Understood Availability
Forecasted Demand Data	Demand Forecasts	Given future time period in question.	[Awaiting SME input.]
Forecasted Additional Information	Demand Flexibility Service instructions		[Awaiting SME input.]
	Weather		Forecast data available and utilised.
	Market Prices[47]		[Awaiting SME input.]
Fixed Scenario Values	Day / Season		Fixed value – determined by other inputs.
	Time of Day		Fixed value – determined by other inputs.

6.3.4.3 Data Quality / Granularity Analysis

As before, data has not been able to be extracted for IBM-run data quality analysis, with comments instead reflecting the current understanding of relevant data quality and granularity.

46 See regulatory consideration point.
47 See regulatory consideration point.

As above, we were unfortunately unable to obtain ESO SME input in this area within the required timeframe. As a result, this section is incomplete.

For weather-related data comments, see section 5.1.4.3.

6.3.5 Regulatory Considerations, Explainable AI, and Process Impacts

Again, there are various points for consideration around explain-ability, impact on existing processes etc.

6.3.5.1 Dispatch Instructions

As for all Input Data models, the previously discussed principles around the ability for humans to understand, analyse, and improve the underlying dispatch instruction logic apply here. In the case of actual demand modelling, arising questions for scrutiny may include:

- In situations where the lowest price units are not utilised, what are the underlying reasons? Is there, for example, a particular area of high forecasted demand that is altering the optimum solution via geographical necessity? To what degree are small changes in demand altering the optimum solution (sensitivity / solution stability analysis)?

6.3.5.2 Use of Market Prices

In the document *Virtual Energy System - Advanced Dispatch Optimiser Google X Comparison (April 2022)*, an ESO Operational Manager points out that, at the time of writing,

> "*The current view from Energy Forecasting is that market price cannot be used in demand forecasting and would require a Grid Code modification to allow it to be used*".

Having said this, it is further noted that historic demand profiles implicitly reflect market pricing information "*as price avoidance behaviour is inherently included in the demand outturn*". The Data Science workstream outlined in the introductory section "Adaptive Model Considerations, Advised Incremental Approach, and Cone of Uncertainty" would help to establish the additional value gained from inclusion of explicit market prices, as opposed to implicit inclusion through demand profiles. Therefore, in detailing the full model specification, it could be decided whether it is worth the required Grid Code modification.

6.3.6 Next Steps

The separately delivered "Roadmap" output will specify next steps in working towards the more holistic longer-term end vision.

However, as indicated above, there are a couple of immediate steps that can be taken to progress this area. These include:

1. Establish whether net demand should be modelled outright, or whether it is of superior accuracy / usefulness to model actual demand and embedded DER contributions separately as described here (see 6.1).

2. Initial Data Science workstream activities (see 4.2.1).

6.4 Adaptive Embedded DER Models

6.4.1 Overview

The Adaptive Embedded Distributed Energy Resource (DER) Models described by Google X Tapestry in the output document Advanced Dispatch Optimizer System Roadmap Report aim to "*estimate the amount and type of embedded DER at each transmission substation*". An underlying understanding of this and the associated impact on demand would enable, through combination with the expected actual demand model, the calculation of forecast net demand.

As noted in the Introduction, embedded DERs are defined as follows:

Embedded DER = Non-instructible resources without any operational metering visible to ESO.

Distinguishing from the DER model above, embedded DERs are crucially not visible, and hence their impact is not measured or well understood at a granular level.

To achieve the high-level purpose, one must understand the presence, use, and associated impact of embedded DERs. In other words:

1. Where are embedded DERs installed?
2. For each type of DER and customer profile class, how is the DER utilised / what is the impact on net demand?

This model group is touched on only very briefly by Tapestry, with very little suggestion as to how this may be modelled, or even what data may be required. Therefore, the below explores some potential methods to answer the above questions, making reference to previously completed work where relevant.

[Note: Regarding an As-Is analysis, there is no known detail around current, in-house, capabilities to forecast embedded DERs in isolation[48]. Therefore, such a section is omitted below.]

6.4.2 Distribution System Operator (DSO) Ownership

An important consideration to raise early here, before discussing the above outlined questions, is the potential role of the DSOs. Whilst this is also discussed as part of the DER models, the lack of metering here arguably places even more emphasis on the DSO.[49]

Given the positioning of these embedded resources in the market infrastructure, it is likely that any activities in this space should be led by the relevant DSO. As before, this would have some implications regarding Explainable AI etc.

The Tapestry report notes, "*the model can be enhanced by working with distribution companies, distributed DER aggregators and other innovation companies to enhance models through access to information*". Whilst Tapestry's description of distribution

[48] Anecdotally, PEF forecasts embedded solar, whilst EFS forecasts embedded wind.
[49] A potential area to explore is the DER visibility innovation project.

company involvement appears to be optional, they are undoubtedly critical to this capability. Indeed, it should be noted that the core projects referenced below were carried out with a DNO, and therefore defined at distribution level.

6.4.3 Where are embedded DERs installed?

This initial question is far from trivial given the suspected prevalence of unregistered Low Carbon Technology (LCT) devices across the network. The first consideration is at what geographical level these devices should be considered. For example, is it most effective to understand these devices at a MPAN-level and then aggregate as necessary, or is it sufficient to approximate by larger area?

One award-winning[50] piece of work which considered precisely this headline question of resource location was the *LCT Detection* project.

6.4.3.1 Case Study: LCT Detection Project

In late 2018, IBM Consulting's AI & Analytics practice undertook the NIA-funded *LCT Detection* project[51] in collaboration with Western Power Distribution and Electralink. Highly relevant to this question of DER location, the purpose read:

> *"By using Electralink's DTS [Data Transfer Service] dataset, combining this with a range of other structured and unstructured data and then applying IBM's Cognitive analytics, the objective is to identify patterns in the data that indicate the presence of EV, PV or other LCTs that had not previously been identified."*

This proof-of-concept project established a method by which previously unknown LCT devices could be detected at a household level, using both structured and unstructured data. A series of different Machine Learning models were developed within an IBM Watson Data Studio environment, and a pathway was presented to support further development and adoption into BAU. For more detail, please view the thorough closedown report[52].

If considering household-level analysis of DER presence, this project provides an innovative method from which to start.

[50] "Data Project of the Year", Network Awards 2020
[51] https://www.nationalgrid.co.uk/innovation/projects/lct-detection
[52] https://www.nationalgrid.co.uk/downloads-view-reciteme/47647

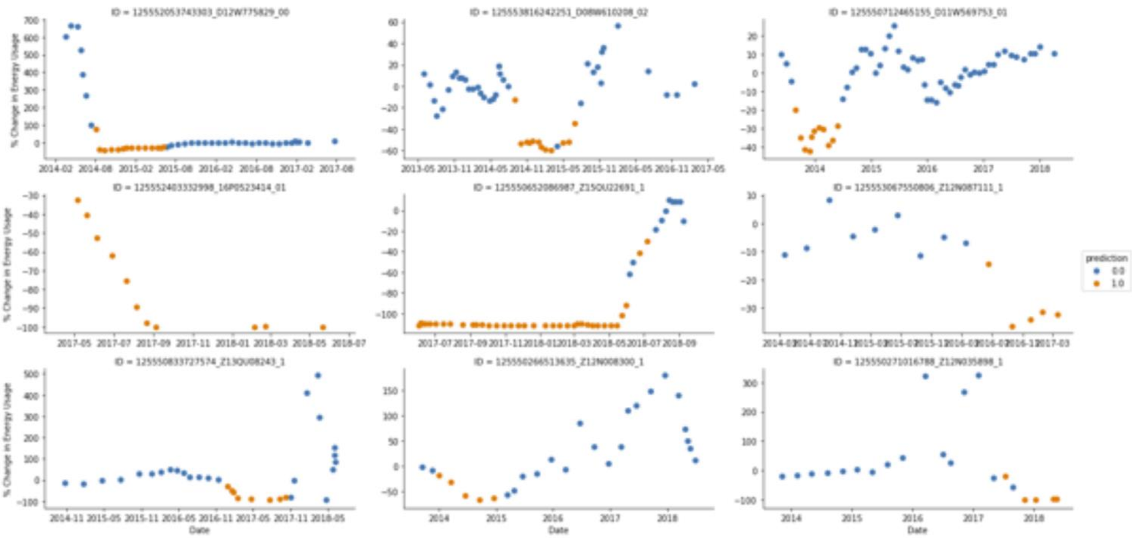

Figure 36: Plots of a random selection of MPANs which the model predicts as having PV installed

6.4.4 For each type of DER and customer profile class, how is the DER utilised / what is the impact on net demand?

Again, this question is far from trivial due to the required segmentation of customers and variability of DER usage. Assuming presence of a DER is known at a given granularity (e.g., household level), useful analysis would require knowledge of how this alters demand. This may be dependent on DER device specifics, tariff type, customer behaviour, location specific information, property type etc.

The exploration of demand variability and the clustering of customers based upon demand behaviour was a central theme of the VM-Data project.

[Note: the VM-Data project focused on net demand. As a result, although a similar methodology could be used to back calculate the impact of DERs by customer segments, it could also be used to look at net demand directly (see discussion in 6.1).]

6.4.4.1 Case Study: Virtual Monitoring Data (VM-Data) Project

Another relevant project of note is the NIA-funded *Virtual Monitoring Data (VM-Data)* project[53], again delivered by IBM Consulting's AI & Analytics practice in collaboration with Western Power Distribution and Electralink. Whilst this project was paused due in part to the outbreak of the COVID19 pandemic, the objectives were:

"Validation and enhancement of the model developed in last year's LCT Detection NIA project; and
Development of a set of domestic half hourly consumption profiles which can be aggregated and used for virtual network monitoring at feeder level, as well as enabling enhanced network planning and demand prediction."

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53 https://www.nationalgrid.co.uk/innovation/projects/virtual-monitoring-data-vm-data

Such a set of domestic half-hourly consumption profiles would be dependent on customer variables, such as house type, location, presence of LCT devices, occupation, etc., as well as more general seasonal variables, including day of the week and month. These consumption profiles provide a more granular understanding of how usage varies by customer (compared to the high-level Elexon profiles), and aggregation would allow better planning of the Low Voltage (LV) network.

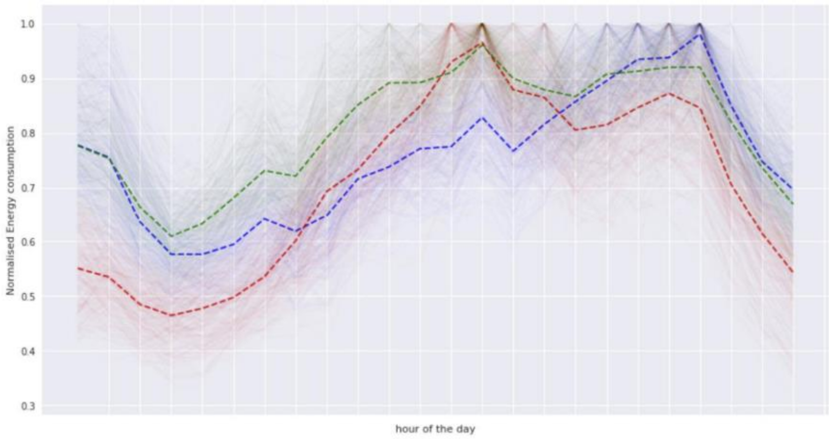

Figure 37: Normalised Consumption profiles showing three clusters for each day at given substation, VM-Data Six Monthly Progress Report

6.4.5 Next Steps

The separately delivered "Roadmap" output will specify next steps in working towards the more holistic longer-term end vision.

However, there are a couple of immediate steps that can be taken to progress this area. These include:

1. Establish whether net demand should be modelled outright, or whether it is of superior accuracy / usefulness to model actual demand and embedded DER contributions separately as described here (see 6.1).
2. Explore potential methodologies for this area, such as those outlined within the innovation projects above.
3. Initial Data Science workstream activities (see 4.2.1).

7 Appendix: Entity-Relationship Diagrams Overview

Logical entity-relationship diagrams are used above to provide a view of potential data input relations and structures. Originally developed in the 1970s, such diagrams are often used in the design and debugging of relational databases as they clearly depict the interconnectedness of different “entities”.

To fully appreciate these diagrams, one must understand the use of different connection types when representing relationships. The below key provides an overview of such connections.

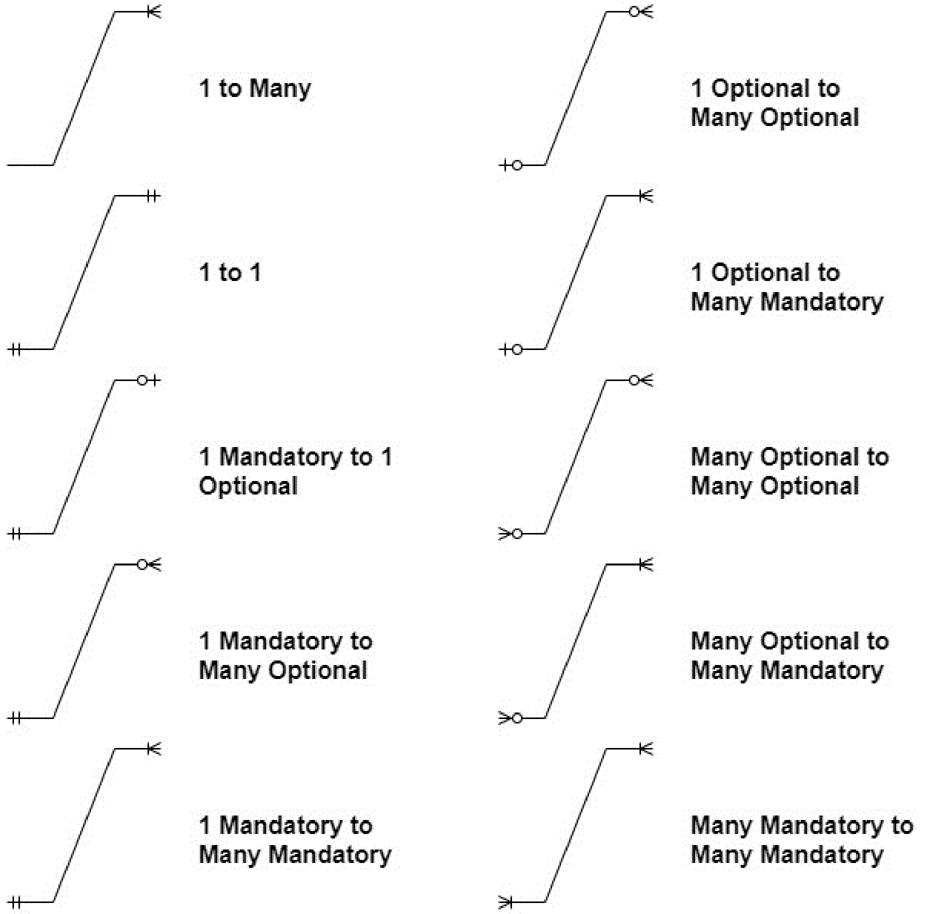

Figure 38: Entity-Relationship Diagram Connection Type Key

There are several different notation convention techniques for this style of diagram. The technique utilised above is one of the most widely used, often referred to as Crow’s Foot notation.

8 Appendix: CIM Representations and Alignment to IBM Data Model for Energy and Utilities

For consistency, completeness, and ease of implementation, one may want to consider the alignment of the above entity-relationship data models to existing standards and blueprints.

The IBM Data Model for Energy and Utilities (DMEU)[54] enables quick development of business applications through the provision of industry-specific data warehouse design models, business terminology and analytics. With regards mapping to the Common Information Model (CIM), DMEU is aligned to CIM standards 61968 and 61970[55]. The third IEC (International Electrotechnical Commission) standard, CIM 62325, is the Markets specific leg and therefore may additionally be of use for ESO.

Giving a basic DMEU mapping example for weather and generator information shows the potential value of such a tool.

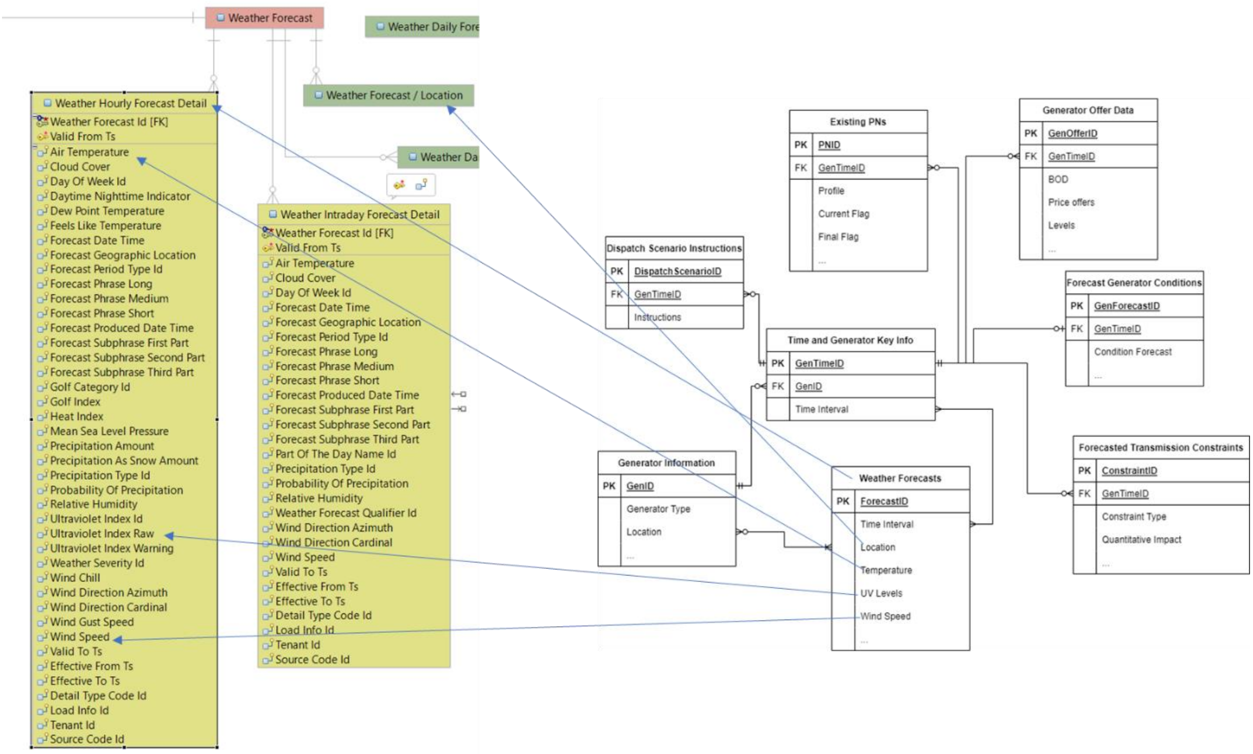

Figure 39: Basic mapping of weather variables to DMEU

[54] https://www.ibm.com/products/data-model-for-energy-and-utilities
[55] More specifically, DMEU is aligned / influenced by CIM 61970-301 and 61968. The Common Grid Model Exchange Standard (CGMES) Library is primarily based on 61970, and as such there is additionally some alignment between DMEU and CGMES.

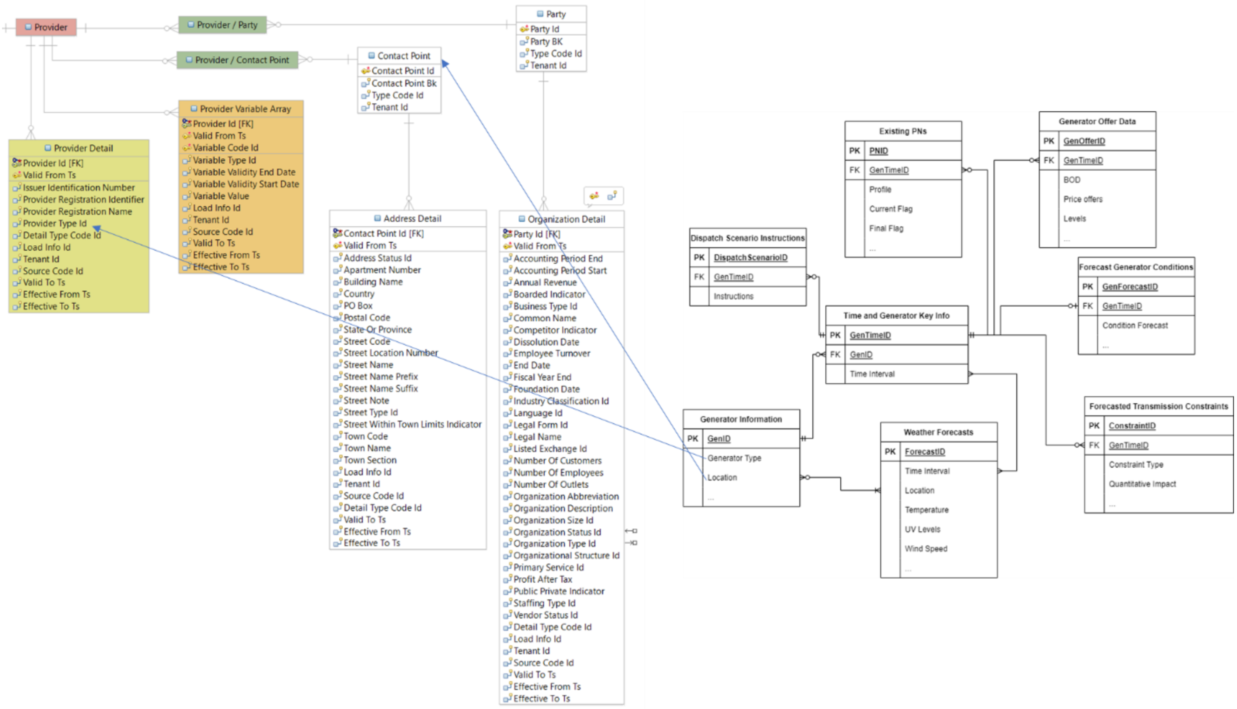

Figure 40: Basic mapping of generator variables to DMEU

[Note: Instances of Generator here could be held as Providers – Providers can also have relationships to Agreements, which could be used to hold any agreements in place between ESO and the generators.]

9 Appendix: Glossary of Acronyms

Table 38: Acronym Definitions

Term	Definition
AI	Artificial Intelligence
API	Application Programming Interface
BAU	Business As Usual
BDO	Bulk Dispatch Optimiser
BM	Balancing Mechanism
BMU	Balancing Mechanism Unit
BOA	Bid Offer Acceptance
BOD	Bid Offer Data
BTM	Behind-the-meter
CCL	Capped Committed Level
CGMES	Common Grid Model Exchange Standard
CIM	Common Information Model
CNI	Critical National Infrastructure
DER	Distributed Energy Resource
DH	Data Historian
DMEU	Data Model for Energy and Utilities
DNO	Distribution Network Operator
DSO	Distribution System Operator
DTS	Data Transfer Service
EFS	Energy Forecasting System
ESO	Electricity System Operator
FFRIC	Firm Frequency Response & Inertia Calculator
FPN	Final Physical Notification
FSP	Flexibility Service Provider
FX	Forecast power
GSP	Grid Supply Point

HVDC	High Voltage Direct Current
IEC	International Electrotechnical Commission
iEMS	integrated Energy Management System
LCT	Low Carbon Technology
LDA	Legacy Dispatch Advisor
LP	Linear Programming
LV	Low Voltage
MAE	Mean Absolute Error
MDA	Modern Dispatch Advisor
MetOffice	Meteorological Office
MILP	Mixed Integer Linear Programming
ML	Machine Learning
MO	Metered Output
MPAN	Meter Point Administration Number
MSE	Mean Squared Error
MW	Megawatt
NCMS	Network Control Management System
NED	National Grid Economic Database
NETA	New Electricity Trading Arrangements
NG	National Grid
NIA	Network Innovation Allowance
OBP	Open Balancing Platform
OEM	Operational Energy Manager
OFTO	Offshore Transmission Operators
OLTA	Offline Transmission Analysis
OSA	Online Stability Analysis
PA	Power Available
PEF	Platform for Energy Forecasting
PN	Physical Notification
PNA	Power Network Analysis

PV	Photovoltaic
RMSE	Root Mean Square Error
RoCoF	Rate of Change of Frequency
SCADA	Supervisory Control and Data Acquisition
SGT	Super Grid Transform
SME	Subject Matter Expert
SQSS	Security and Quality of Supply Standard
TO	Transmission Operator
TSO	Transmission System operator
UV	Ultraviolet
VES	Virtual Energy System
VM	Virtual Monitoring
WiMP	Wind Metered Power
XAI	Explainable Artificial Intelligence