PLEXOS Validation 2019-25 and Backcast

Input Validation and Backcast Report

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Abbreviations and acronyms

CPF	Carbon Price Floor
CPS	Carbon Price Support
CRM	Capacity Remuneration Mechanism
DA	Day Ahead
DAM	Day Ahead Market
DC	Directed Contracts
DSU	Demand Side Unit
ECA	Economic Consulting Associates
ENTSO-E	European Network of Transmission System Operators for Electricity
ESB	Electricity Supply Board
EU ETS	The European Union Emissions Trading System
EWIC	East-West Interconnector
FOR	Forced Outage Rates
GB	Great Britain
GCS	Generation Capacity Statement
I-SEM	Integrated Single Electricity Market
MIP	Mixed Integer Programming
MMG	Market Modelling Group
MMU	Market Monitoring Unit
NI	Northern Ireland
PSO	Public Service Obligation
RAs	Regulatory Authorities
ROI	Republic of Ireland
RR	Rounded Relaxation
SEM	Single Electricity Market
TLAF	Transmission Loss Adjustment Factors
VOM	Variable Operation and Maintenance

Executive summary

Scope of work

In September 2019 ECA was appointed by the Regulatory Authorities (RAs) to complete a backcast of the current SEM PLEXOS model (2018-2023) and to update and extend the validated SEM PLEXOS model to cover the period 2019 – 2025.

Data gathering, stakeholder engagement and quality assurance

Data was gathered from generators, TSOs, the RAs and external sources to ensure the most recent information is used in the model. This included technical generator data, commercial generator data, future outlook projections, commodities, fuel adders and the most recent wind and demand profiles.

Throughout the project, engagement with market participants was carried out through emails, meetings and an industry workshop on the 9th of December 2019. This ensured that participant comments and concerns were captured and incorporated where appropriate in the validation exercise.

Diligent data quality assurance has been carried out throughout all stages of the data gathering processes by validating data for completeness and correctness.

Model validation to include latest data and extend model to 2025

Following the data gathering exercise the earlier model was updated and extended to 2025. This incorporated the latest projected information such as retirement dates, commissioning dates, demand projections and wind capacity projections. Demand and wind profile data was likewise updated to reflect the most recent data available. Outages were updated with the TSOs latest projections and extended to 2025.

Sensitivity analysis was carried out to test some of the modelling parameters such as start-time, look-ahead, PLEXOS version and uplift algorithms. Similar analysis was carried out on the backcast before recommending the final adjustments to be carried across to the validated model.

Backcast to verify model robustness against I-SEM historical market outcomes

This is the first model backcast to be carried out since the I-SEM launch in October 2018. The period for the backcast is limited in length and recently changed markets usually require some years to mature and settle. As part of this exercise, market condition inputs were set to match historical actual values in the model including demand, wind and commodities.

Where the backcast analysis identified clear options for improving the model then these were recommended as part of the overall model update. One of the modelling approaches examined and adjusted extensively was the modelling of Great Britain (GB) and interconnectors as the previous modelling approach gave poor representation of interconnector flows.

However, for some key areas for potential improvement a single year of data was insufficient to recommend substantive changes. These relate to instances of high market prices correlated with low or volatile wind generation, to the benefits of MIP implementations and to changes to the uplift and mark-up methodologies across the summer months. Each of these aspects had a strong seasonal component in the appropriateness of modelled outcomes. In these cases, the outcomes and potential causes for these are discussed, but no change implemented. It is recommended these issues to be monitored going forward to identify whether or not a repeatable and predictable pattern emerges.

Recommendations from backcast and validation exercise

The primary model updates include the update of the technical and commercial parameters to the latest verified values. The percentage of generators which had changes included 36% for heat-rates, 82% of start and VOM costs, 24% of operational costs. All updates from the most recent Generation Capacity Statement (GCS) 2019 – 2028 are carried over as they represent the latest and most robust outlook from the TSOs.
The resulting recommendations from the validation and backcast include:

- Changing the model start-time from 6am to 11pm.
- Updating the PLEXOS model version from 7.3 to 8.1.
- Adopting a new GB modelling approach which follows a heat-rate regression against GB gas prices with horizontal segmentation and intermittent generation included.
- Removing wheeling charges from the model.

The following settings were assessed, and the current methodology recommended to be retained:

- 6-hour look-ahead
- Korean uplift algorithm
- Current mark-up methodology
- RR modelling methodology

1 Introduction

1.1 Scope of work

In September 2019, ECA was appointed by the Regulatory Authorities (RAs) to complete a backcast of the SEM PLEXOS model and to update and extend the validated SEM PLEXOS model to cover the period 2019 – 2025.

Similar model validation exercises have been carried out on an annual basis by the RAs. The two most recent model validations were carried out in 2017 and 2018. The earlier of these explicitly considered the prospect of market changes that would be seen in the Integrated Single Electricity Market (I-SEM), the latter of these was undertaken after the I-SEM market trials (associated with I-SEM implementation) but did not use the trial market-data. When considering model settings both exercises were constrained by the unavailability of operational market data.

For these same reasons a backcast exercise comparing modelled outcomes against real market data had not yet been undertaken since the I-SEM launch on the 1st of October 2018.

1.1.1 Overview of the I-SEM PLEXOS model

The RA's I-SEM PLEXOS model is a representative model of the all-island electricity system across Republic of Ireland (ROI) and Northern Ireland (NI).

The model style is a generation cost driven model[1], where generator bids and offers are assumed to be formed from a combination of unit-based underlying fuel, running, and start costs alongside an incentive to make a profitable margin on any generation sold. On aggregate this model style typically provides a strong representation of the underlying long-run cost drivers for the market but does not explicitly take into account the risk-exposure of individual generators and retailers to different market price/volume outcomes. Therefore, it would be reasonable to see a fairly strong representation of the aggregate

[1] The key alternative traditional model-types would be 1) a model incorporating theoretical market-power based behaviors, examples of these include Bertrand and Cournot models, 2) a reduced form model which predicts outcomes based solely on external market changes impacting the system 3) statistical models (e.g. time-series modelling based on historical outcomes) and 4) machine-learning algorithms. In the SEM market-power based behavior models produce unrealistic results as exercise of market power is mitigated in practice by regulatory intervention and the threat of further regulatory intervention. All three other potential options would not be advisable for modelling the SEM as they could not produce robust results when trained solely on a single year's worth of market data.

An alternative variation would be to incorporate portfolio modelling into the model framework – this assumes market behaviours are impacted by the portfolio of contracts and generation facilities owned by each company, and their corresponding exposure to prices. This assumes that generators will deploy their generation assets so as to optimise their profitable returns on their full portfolio, not treating each asset independently. This may not be appropriate for the SEM given the unit-based nature of CRM payments. Likewise, this would require a significantly increased level of public contract visibility in order to maintain and develop such a model.

market outcomes. The model is solved by being broken into subproblems, each subproblem solution represents a daily market outcome at an hourly granularity. A Rounded-Relaxation (RR) style unit-commitment algorithm provides unit-commitment decisions for each unit across each day. The forward-looking model uses five wind and demand profiles to construct a range of possible behaviours and expected future outcomes.

The model has several key roles in the market including:

- Capacity Remuneration Mechanism (CRM) modelling:
- Directed Contracts (DCs) modelling.
- For strategic analysis by the RAs.

As part of this exercise the model is to be validated, both in terms of inputs and model settings; and based on a backcast against actual market data.

Box 1 Reference to SEM vs I-SEM

Throughout the document there is reference to SEM and I-SEM. Although I-SEM refers to the implementation of the "Integrated Single Electricity Market" which went live on the 1st of October 2018, the market thereafter is still referred to as the "Single Electricity Market" after this date. For the purposes of this document it is assumed that SEM refers to the period prior to the go live date in October 2018 and I-SEM to the new market arrangements since then.

1.1.2 Input data validation

This exercise has included a review and validation of the input data which underpins the representation of the I-SEM market fundamentals in the model. These are a set of core generation profiles, load profiles, costs and technical characteristics which will drive market outcomes.

The desired outcome when refreshing and reviewing generator data is to ensure that, wherever possible, the model data strongly aligns to how participants view their own costs when making commercial decisions about how to offer to the market. The trading methods used to recover these costs alongside a profitable margin may differ between participants. Nonetheless across the wide variety of market conditions and possible scenarios any trading strategy must ultimately align with these revenue requirements to ensure a company maintains profitability.

When refreshing system data, the core goal is ensuring a reasonable representation of net demand[2] which is exposed to the I-SEM market mechanisms. In this case the method includes updating representations of aggregate system wind, demand, embedded generation and interconnector availability. This relies on the expectation that any over-estimate of demand presented to market will be compensated for by the inclusion of the corresponding embedded generation or wind which will meet that load requirement so that it does not get cleared through the market.

[2] Net demand is the total supply needs procured through the centralized system, after local elements such as embedded generation and losses have been taken into account.

Although commodity data updates are performed as part of the input validation, these comprise only a small component of the model validation exercise. It is important to update local elements which differentiate commodity pricing such as fuel adders. Nonetheless, many of the fuel commodities which are priced into the model are exposed to significant market volatility and will need to be regularly updated by model users to ensure modelled market results reflect current market conditions.

Key input datatypes that have been validated and updated where necessary are presented in the following table.

Table 1 Input data validation categories

Category	Changes
Generation plant data	Plant commissioning dates
	Plant retirement dates
	Fuel types (primary and secondary)
	Capacity
	Heat-rates
	Forced outages
	Planned outages
	Mean time to repair
	Ramp rates
	Min up and min down times
	Start-up characteristics
	Variable Operation and Maintenance (VOM) costs
	Operational costs
	Storage and Hydro
System data	Wind (capacity outlook, profiles and capacity factors)
	Demand (peak and total demand outlook and profiles)
	Interconnectors (including contracted capacities)
	Demand Side Response Units (DSUs)
	Transmission Loss Adjustment Factors (TLAFs)
	Embedded generation
Commodities	Fuels
	Exchange rates
	Carbon assumptions
	Fuel adders
	Updates to reflect changes in plant fuel arrangements

The input validation is focussed on the building blocks as presented in Table 1, which form the foundation of the model. The focus is on ensuring there is a sound basis for commercial decision-making, and that data is well-aligned with participants own estimates of their willingness to encounter costs, alongside the transmission and market operators own estimates of the capabilities of the interconnected system.

1.1.3 Backcast validation

The backcast contrasts with the input validation as it takes a top-down approach to model validation. The key arbiter of success is whether or not the modelled results make a reasonable approximation of the aggregate system results (namely price, generation, interconnector flows and aggregate generation by fuel) from the live market over the specified historical time period.

Typically, a backcast would be undertaken on a multi-year sample before introducing significant model changes. This ensures that modelling analysis, and market behaviour analysis can eliminate the impact of one-off conditions on participant behaviours such as:

- Low, medium or high seasonal demand profiles in particular years.
- Low, medium or high seasonal wind profiles in particular years.
- Years with unusual generator or system characteristics, such as significant plant outages or interconnector limits.

An appropriate time-sample for analysing the fundamental drivers of market outcomes under steady-state and across a range of market conditions would be between three to five years.

However, since the I-SEM launch was just over 12 months ago, in this case the calibration to market outcomes includes only 12 months of data. Over this range it would be reasonable to see only a moderate representation of the aggregate annual market results.[3]

Beyond this, where significant variation is seen, there is now an opportunity to examine some of the more detailed initial bid and offer data. This data needs to be treated with caution when considering any changes to the modelling methodology as it is a limited snapshot under a particular set of market conditions. There is therefore a significant risk of overfitting the model with market conditions seen to-date rather than the range of market outcomes which would be expected over a range of future market conditions.

1.1.4 Sensitivities calibration

As part of the backcast exercise historical inputs are used to test the model's performance against actual I-SEM market data (price, generation by fuel type, interconnector flows etc.). This includes the calibration and testing of certain sensitivities (refer to Table 2). These are typically incremental improvements, rather than large changes. However, they can have a significant impact on the model solution.

Where potential changes are identified they must first be verified to be driven by market fundamentals. Then potential changes must be proven to demonstrably show an improvement to the model outputs against actual historical data over a range of potential

[3] Based on international experience for a backcast analysis the differences between annual aggregate market results and modelled results would be expected to sit roughly within a +/-5% threshold over a 3-5 year time-frame once event-based outliers are taken into account. Since this calibration is over a 1 year time-frame, it is reasonable to see higher volatility than this.

system outcomes. Only once they have passed both of these gates are they considered candidates for inclusion in the newly updated I-SEM PLEXOS 2019-2025 model.

To calibrate the model, a number of market settings are adjusted to different likely values. The impact of these changes is then retested on the solution across both the forward-looking model and the backcast. This allows quantification of the impact a change would have on the accuracy of historical market outcome replication. At the same time by testing the proposed change against the forward-looking model it is possible to gain greater insight into how the influence of that sensitivity on market solutions may evolve as the make-up of the market itself changes.

Examples of the sensitivities explored are summarised in the following table. Any accepted changes are integrated into the backcast and forward-looking models.

Table 2 Examples of sensitivities tested

Parameter	Sensitivity tested
Start-time	Tested the update of the start-time from 6am to 11pm to align with actual Day Ahead Market (DAM) conditions
Look-ahead	Explored smaller and larger values of the look-ahead currently set at six hours
PLEXOS version	Tested the effect of upgrading from PLEXOS version 7.3 to 8.1
Uplift	Tested the effect of differing uplift methodologies
Solver mode	Explored the impact of using Rounded Relaxation (RR) or Mixed Integer Programming (MIP)
Great Britain (GB) modelling	Explored different methodologies of modelling the GB market

1.1.5 Fundamental market modelling philosophy

Since the market plays an active role in long-term capacity remuneration decision-making it is most appropriate for it to continue to maintain the pure economics perspective following long-term steady state cost behaviours (and associated uplifts). This allows it to provide a sound basis for long-term pricing trends and future expected dispatch patterns, including those for future proposed plant.

The reasons for this are partially based on an underlying economic philosophy, and partially based on pragmatic considerations.

In terms of the modelling philosophy over the long-term, it is reasonable to expect the pricing and offer behaviours which are exhibited in the market to reach a steady state which allows generators to cover their short run marginal costs and underlying long-term costs. Although short-term trading behaviours are likely to exhibit greater variance in achieving this outcome, the cost drivers remain constant. Correspondingly, the required revenue implicit in different market behaviours will also remain constant. The short-term trading behaviours will necessarily change as the traders, trading managers, and portfolio positions of different participants change. The core cost drivers will continue to be driven by the same fundamental elements.

On the pragmatic side, even if you assume that short term trading is likely to reach and maintain a steady state of behaviours, then for each of these traders, a significant quantity of data will have to be maintained and reviewed regularly to create models which can represent the core behavioural drivers. This would require multiple years of trading data under a range of conditions. For an existing generator this may eventually become possible once the changes from I-SEM have been in operation for an extended period of time.

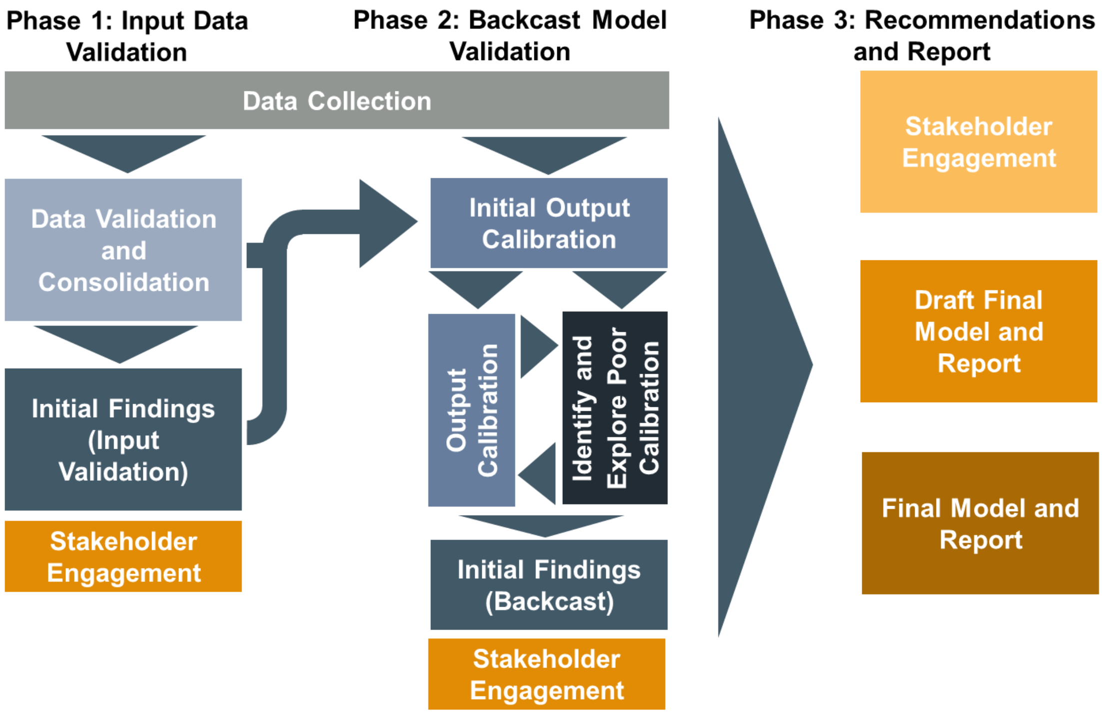
Even then this may not be an advisable solution unless a highly automated data solution could be found. This is due to the high levels of model maintenance that would be involved. Likewise, this level of data will also never be reasonably available for proposed new generation/storage/DSUs/assetless units etc. across the forward-looking timeframe.

For these reasons, significant alternatives to the under-pinning modelling philosophy were not considered as this style of substantive change as out-of-scope for the current exercise. All model inputs and outcomes were evaluated within the paradigm of long-term steady-state costs as the primary driver of aggregate market offer and bid behaviours.

1.2 Approach and methodology for validation

In order to address the tasks described above, this assessment was carried out using a phased approach. The project was split into three phases as illustrated in the figure below, engaging with stakeholders at key points across the process.

Figure 1 Methodology overview



1.2.1 Data collection

The initial stage across both phases was focussed on data collection. The data collection exercise included sourcing data from generation market participants, from the system operator, market operators, interconnector owners and the RAs. A high-level breakdown of data sourcing is shown in the table below:

Table 3 Data sourcing

Category	Data collected	Sources
Generator technical and commercial data	Commissioning and retirement dates	Generators, Generation Capacity Statement (GCS) 2019, capacity and DS3 auction results
	Fuel type	Generators
	Capacity	Generators
	Heat-rate curve	Generators
	Forced outages	Generators
	Ramp rates, min up and min down times	Generators
	Start characteristics	Generators
	VOM costs	Generators
	Fuel adders	Generators and public data
	Storage technical details	Generators, capacity auctions, and DS3 auction results
System data	Wind profiles	TSOs
	Wind capacity outlooks	GCS 2019
	Demand profiles	TSOs
	Peak and total demand outlook	GCS 2019
	Interconnector (historic flows and contracted capacities)	TSOs and RAs
	Planned outages	TSOs
	DSUs	Capacity auction results and historical bid offer data from RA Market Modelling Unit (MMU)
	TLAFs	TSOs
	Embedded generation	TSOs
Commodities	Fuels	RAs
	Carbon	RAs
	Exchange rates	RAs
	Fuel adders	Generators and published data
Historic data (for backcast)	Wind	TSOs and RAs MMU
	Demand	TSOs and RAs MMU
	DA Commodities and exchange rates	RAs
	Outages and output restrictions	TSOs and RAs
	Historical interconnector DAM transfer capacities	TSOs
	Integrated Single Electricity Market (I-SEM) and GB DAM wholesale electricity prices	RAs
	Interconnector flows	TSOs
	Generation per fuel type and per unit	TSOs and RAs MMU

1.2.2 Data validation and consolidation

Phase 1 and Phase 2 both included significant data requirements from an array of sources. Following data collection, analysis of the supplied data was performed, alongside analysis of how well it fit with the existing model and market environment. To validate the alignment of the data provided with wider market principles in most cases inputs primarily required comparison to data to available secondary sources to ensure strong alignment. Where an appropriate secondary source was not available, data was evaluated against typical or historical values for the datatype.

1.2.3 Initial findings (input validation)

To develop the initial findings, the aggregate impacts of the proposed data changes were examined. This analysis for Phase 1 was focussed on identifying whether the updated values continued to be an appropriate representation of system drivers. This primarily focussed on exploring the scale and impact of each incremental change to the model data characteristics. Where value changes had little impact, or the impact seen was predictable and reasonable based on changes to the data then it was viewed as a reasonable outcome and incorporated into the model. Based on high-level bilateral stakeholder conversations a set of expected market behaviours were identified alongside insight into whether or not the outcomes broadly aligned with stakeholder observations of the market to date.

1.2.4 Initial output calibration

The Phase 2 backcast initial outcome validation followed a similar approach to the input validation in Phase 1 but instead of calibrating changes against existing modelled outcomes, the calibrations were against historical market outcomes. Model inputs and parameters are then calibrated to simulate historical market behaviour in the most appropriate way whilst maintaining reasonable model running times. Where significant adjustments were made so that backcast outcomes were more strongly aligned with market outcomes then those changes were also evaluated for inclusion in the forward-looking model data inputs.

1.2.5 Output calibration/identify and explore areas of poor calibration

Once the high level aggregate initial output validation was complete the focus for Phase 2 shifted to identifying specific areas of poor calibration in order to review and revise the approach taken. This included a focus across particular time periods, or across particular system elements. The most significant example of this was the case of interconnector flows to and from GB. The backcast comparison identified that these were significantly less well-calibrated to market outcomes than other elements. A number of different possible model representations were identified to reflect the same underlying system data and reviewed to evaluate the benefit of each of the possible methods.

As part of this stage of calibration, several sensitivities on model settings have been explored, including evaluating the impact of changes to look-ahead values, start-time and various other system representation elements.

To facilitate stakeholder input, an industry workshop (9th Dec 2019) was undertaken during this stage in the process. This enabled both identification of stakeholder concerns regarding the work to-date, and valuable insight into some of the calibration issues being addressed. Based on stakeholder feedback aspects of the model which required further exploration and analysis were identified.

1.2.6 Initial findings (backcast)

Developing the initial findings for the backcast included an evaluation of the range of proposed options for different data elements. Each of these were evaluated against their strength of fit for market behaviours over the historical time period as well as their maintainability. Where relevant the impact of proposed changes on modelling times was also explored.

1.2.7 Finalisation of the model and model reports

Once a reasonable range of calibration options for each of the key areas was identified, the model validation was completed enabling the drafting of the model validation report and the confirmation of the final model settings.

1.3 Quality assurance

Data forms the backbone of this modelling exercise and therefore a diligent quality assurance has been carried out throughout all stages of the data gathering processes.

Generator technical and commercial data

Templates were sent out with instructions to all generator companies to provide their most recent and accurate technical plant data per unit. Likewise, some cost-based data for generation units was also collected from generators through these templates.

A template requesting any views on fuel adder updates was also provided, as well as a wider set of questions around the relationship between generator operational requirements and their commercial drivers (e.g. contracts, LRSAs etc.).

The data collected from this process was reviewed for reasonableness. The focus was firstly whether any changes to existing data were reasonable and had a strong underpinning rationale. The secondary focus was evaluating all data held for different generation plants (including that which was unchanged) to ensure they were reasonably closely aligned to standard industry representations of similar plants. Where data provided deviated significantly from expected ranges, clarification was requested on the reasoning to ensure best possible representation in the model. The final data collated was then provided to the RAs for their review.

System Data

Up-to-date system data was obtained from official market sources including System Operators EirGrid and SONI as well as the Market Modelling Group (MMG) and the Market Monitoring Unit (MMU) teams of the RAs. Continuous engagement with these stakeholders allowed for the gathering of the most recent and relevant data both for validation and backcast purposes. Where possible data was reviewed against additional external secondary sources such as the European Network of Transmission System Operators for Electricity (ENTSO-E), market monitoring frameworks in GB, and/or market sources from a second market operator organisation.

Input Processing

All data received and used was validated to ensure it aligned with expectations before being inputted into the model. This included sense checks against historical or previously used data, as well as identification of erroneous or incomplete data. Where data with inconsistencies was identified it was further investigated with the source and validated before application.

Moreover, once the data updates were input into the model, then each set of updates were tested individually in step changes to ensure that on aggregate the system impacts aligned with overall expected system outcomes.

2 I-SEM

The I-SEM launch has significant impacts on the model validation across a variety of areas.

2.1 Bids and offers

The I-SEM launch has fundamentally changed the way participants bid and offer into the electricity market, both in terms of the structure of these bids and offers, and in terms of the content.

The structure of bids and offers has shifted significantly as the new market structure introduced a Day Ahead Market (DAM) and intra-day markets. This introduces changes to the key times at which traders must make crucial tactical decisions, and the level of knowledge they will have when making those decisions. Likewise, these allow traders to incrementally reveal the nuances and elasticity of their individual supply and demand curves.

An additional structural component which was introduced by the I-SEM is that participants are provided with the option of using a complex bid-type with a minimum income condition specified as a separate component. This element provides flexibility for participants to simultaneously signal price differentiation between different hours of the day, and also signal their unwillingness to incur start-costs in a day if it will only provide a low total income across the day.

A key change in terms of bid and offer content in the I-SEM is that participant offers are no longer explicitly drawn from a simple generation cost basis (plus uplift) but can be set by participants based on their strategic pressures. This allows generators greater flexibility in determining and implementing different bid strategies.

2.2 Scheduling algorithm

The market clearing engine for the newly established DAM is the EUPHEMIA algorithm. The EUPHEMIA algorithm is used exclusively for establishing the DAM schedule. This algorithm is already operating across a number of different European electricity markets.

Alongside fundamental algorithmic differences, one of the key changes resulting from the use of EUPHEMIA is that there is greater simplicity in how market participant information is presented to the scheduling algorithm. Specifically, there is no explicit consideration or documentation of generator technical characteristics or associated commercial parameters.

It is assumed that participants will manage their own risks and costs associated with elements such as start costs, no-load costs and minimum run times. The bids and offers which are then presented to the market by participants will have internalised some commercial estimate of the potential costs these elements could present. This can either be through the mechanism of sculpting simple hourly orders (represented as price/quantity pairs for a given hour) or with the additional component of a minimum income condition.

The minimum income condition represents the minimum aggregate income a generator requires to be dispatched for within the daily solve in order to be included in the market dispatch solution. If this threshold is not met, then that generating unit will not be dispatched into the DAM scheduling outcome.

While the move to the EUPHEMIA algorithm means a stronger alignment of the SEM with other European markets there are still unique characteristics. The most notable of these is that participants continue to be required to shape all bids at a unit-based level. The majority of EUPHEMIA based markets additionally allow portfolio-based bidding. The continuation of unit-based bidding however will also result in a continuation of the focus on unit-based costs. The management of the risk and cost element trade-offs for these has shifted from the market dispatch algorithm onto the participants themselves.

The PLEXOS model does not attempt to directly reflect the different EUPHEMIA order-types, but instead the underlying costs which will also drive the price/quantity pair formation which participants bid into EUPHEMIA. These differences between the market dispatch algorithm and the tools used to replicate the outcomes are common across a wide variety of international markets, and despite the difference in algorithm will usually result in very similar price and generation outcomes. For the DAM this appears to be the case under most (but not all) market conditions, for further detail see sections 7 and 8 for the backcast results.

2.3 Impact on model validation

With the launch of the I-SEM the structure of the electricity markets changed substantially, and so there is a clear discontinuity between historical market-based data sources before and after the I-SEM launch. The most notable of these market-based outcomes would be historical market offers and historical market prices. Nonetheless the physical supply and demand elements which underpin the market continued to be similar – the generation fleet and consumers are still broadly the same.

As a result of these changes when validating the model inputs and outputs it was evident that pre-I-SEM data including historical bids/offers, dispatches and proportion of different sources offered through the market are no longer appropriate for use in validating the model. Although some of these data-sources can still be used as a high-level sense-check these data sources are based on a different set of market structures and should be approached with caution.

As the model still requires a range of historical demand/wind scenarios it was necessary to use a set of historical sources which reflect the gross quantities of each of these elements which will drive the market outcomes.[4] These data-sources will reflect gross demand, gross wind values and gross embedded generation, each of which will drive some component of the price formation. Once these gross inputs elements net off against one another then a residual supply and demand curve will be formed – this includes the core price-setting market elements. The set of costs, risks and value associated with these generation supply curves are the same as those which underpin bid formation in the DAM solve. The marginal

[4] In this instance gross system inputs are represented by whole-of-system actual data as developed from SCADA readings or directly supplied by EirGrid.

price-setter from the resultant supply curves will therefore be equivalent. Thus, the price formation in the model and in the market will resolve in a similar fashion. This expectation was further validated by a backcast comparison between the PLEXOS model outcomes using historical gross inputs, and a model using DAM offered inputs for wind and demand. The results were very similar in terms of accuracy in replicating historical market outcomes.

The model validation and backcast were necessarily limited in accuracy due to the 12-month timeframe since market launch. This means that the new market data sources are not yet very robust.

- There has only been a single sample of each month's trading behaviours, which gives a sample of between 19-23 workdays, and 8-12 non-workdays for each month.
- The majority of stakeholders spoken to during the input validation did not believe the market had yet reached steady state outcomes. Market participants can reasonably be expected to exhibit learning behaviours during this time period as the seasons change and the demand and wind pressures on the market likewise evolve. They will also be observing and learning from the behaviours shown by other participants.
- Given the small sample of behaviours under a single set of market conditions, it would be inappropriate at this stage to shape model input data explicitly based on market bids and offers, or on the levels of market participation seen for elements such as wind.

These aspects impact on the input validation component, since they indicate the I-SEM is a recently launched market still developing to a steady state. An approach to market modelling based on the underlying cost-drivers and aggregate system outcomes is most likely to closely and reliably predict future behaviours for such a market.

These aspects likewise impact on the backcast component. It is difficult to categorically validate a model against historical market outcomes with a single year of data. If recent historical data is used to shape model outcomes too strongly this can result in model over-fitting. A model which is over-fit to exactly replicate the market outcomes from a specific market year will not be appropriate to model future expected years.

In a number of these areas where over-fitting is a risk the modelled behaviour was reviewed and compared to the market behaviour. This process is designed to identify risk areas for future analysis. If these trends continue to be seen as the market develops then it is an area where the model will need to be adjusted to better fit market outcomes.

3 Generation plants

3.1 Commissioning and retirements

The inclusion of generation commissioning and retirement dates in the model is intended to provide a close representation of firm market capacity. This means that it will reflect capacity which can be assumed to be committed to market, as signified by the outcomes of the T-4 2022-23 capacity auction and 2018 DS3 frequency response auctions (services to be delivered May 2021). It will also reflect firm generation capacity retirement decisions, as announced to market.

The primary source where these elements are consolidated is in EirGrid's most recent GCS. However, this was supplemented by a review of the T-4 2022-23 capacity auction outcomes, DS3 frequency response auction outcomes, public market announcements and specific information sourced from the generators themselves. Timings of new build and of retirements were based on those described in the T-4 2022-23 capacity auction outcomes unless the generation participant provided more specific data. All retirements have been discussed and agreed with the RAs.

While batteries from the DS3 frequency response auction are included at this time these batteries may be dispatched on a shorter timeframe than the hourly DAM. It is recommended their inclusion is reviewed regularly as more information on their characteristics becomes available.

Retirements

The following table provides a summary of generation unit retirements that have been revised or introduced to the model since the previous validation exercise.

Table 4 Plant retirements (updates from previous model only)

Plant	Capacity (MW)	Closure	Comment and key difference
Aghada (AT1)	90	2023	IED limited life-time derogation. Did not clear the CY2018/19 T-1 auction
North Wall 5	104	2019	Closing in September 2019 to be repowered
Moneypoint	885	2025	Assumed in latest GCS on the basis of Moneypoint not being compliant of the Clean Energy Package of 550gCO_2/kWh
Kilroot ST1	238	2024	AES has indicated that it will reduce to 199MW from mid-2020. As per latest GCS it is assumed not available after 2024 due to restrictions on coal-firing
Kilroot ST2	238	2024	AES has indicated that it will reduce to 199MW from mid-2020. As per latest GCS it is assumed not available after 2024 due to restrictions on coal-firing
West Offaly	140	2020	Announced closure at the end of 2020
Lough Ree	93	2020	Announced closure at the end of 2020

Commissioning

The following table provides a summary of the new plants that have been added to the model since its previous validation exercise.

Table 5 Plant commissioning (updates from previous model only)

Plant	Capacity (MW)	Start
ESB North Wall 5 GT	118	2022
ESB North Wall 4 GT	118	2022
ESB Ringsend Gas Flexgen	70	2022
ESB Poolbeg Gas Flexgen	70	2022
ESB Corduf Gas Flexgen	70	2022
ESB Poolbeg 2hr Battery Storage	75MW (39MW de-rated capacity in GCS)	2022
ESB Southwall 2hr Battery Storage	30MW (17MW de-rated capacity in GCS)	2022
ESB Inchicor 2hr Battery Storage	30MW (17MW de-rated capacity in GCS)	2022
ESB Aghada 1hr Battery Storage	19MW (7MW de-rated capacity in GCS)	2022
Porterstown Battery Storage	30MW (20MW de-rated capacity assumed)	2022
Kilmannock Battery Storage	30MW (20MW de-rated capacity assumed)	2022
Gorman Energy Storage Station	50MW (40MW de-rated capacity assumed)	2022

The key differences include:

- Introduction of five ESB gas generators in 2022 with a total capacity of 446MW that have been successful in the recent CY2022/23 T-4 capacity auction.
- Introduction of seven battery storage units with a total capacity of 207MW in 2022 based on most recent capacity auction results and DS3 frequency response auctions.

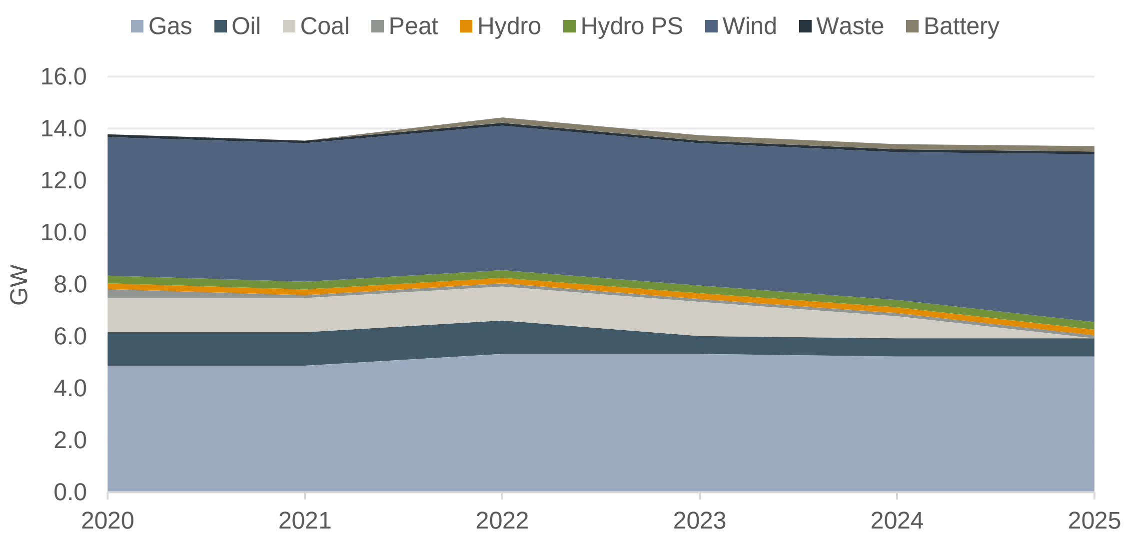
Aggregate installed capacity

Generation installed capacities per fuel category are illustrated in the figure below showing the capacity updates described so far. In general coal, peat and oil plants are retiring across the modelling horizon. New generation capacity tends to focus on a mixture of gas, storage and wind.

As noted above the total capacity represented in the model only includes firm retirements and commissioning based on proposed plants which are viewed as committed to market. This mirrors the latest available data from GCS, auctions and the RAs. Future auctions may identify more capacity to come online post 2022 to offset retirements and allow for a healthy capacity margin with rising demand.

By representing only firm committed decisions for new build and retirements then the PLEXOS I-SEM model can provide a strong signal on forecast areas of market stress. This allows potential new entrants to identify the potential value of possible new builds with different generation profiles.

Figure 2 Installed capacities



3.2 Technical and commercial data

The representation of technical and commercial data in the PLEXOS model is one where expected generator bids and offers are built up based on key technical unit-level data and associated expected costs of different unit behaviour. This means that the technical and commercial data inputs must be a strong representation of the marginal running costs of a committed unit, as well as including a strong representation of the start-up costs, and operational running characteristics of each plant.

For existing plants, these market characteristics are usually sourced from generators and reflect their best estimate of the operational realities of a given unit. For new proposed plant these characteristics need to be developed from a generators prospective view of expected operational characteristics. In practice the actual operational performance of the plant may allow the plant to over-perform or under-perform against these specifications once it enters the market.

It is essential that technical and commercial data values are a close representation of the way participants view their plant running characteristics. The I-SEM PLEXOS model is most effective when it reflects the data which participants are basing their commercial decisions off when deciding what to offer to market, and at what price.

Following the quality assurance process described in section 1.3 the technical and commercial plant data, directly sourced from participants, was updated per unit in the model. The updates reflect any recent or future expected changes to running characteristics. In summary, the data that were validated and updated accordingly were:

- Fuel type
- Capacity
- Heat-rates
- Forced outages and mean time to repair
- Ramp rates and min up and min down times
- Start-up characteristics
- VOM costs
- Operational costs

There were a number of key changes to technical and commercial generator data. Based on engaging with stakeholders on the specific large changes these were mostly driven by re-evaluation of key cost drivers. Related changes included increased granularity of data or re-evaluation of start-up characteristics.

The following table illustrates the percentage of generators that had a change in the main technical and commercial characteristics. The values below do not reflect the scale of the change, in many instances this was relatively small.

Table 6 Key technical and commercial generator updates

Key generator parameter changes	% of generators with changes
Heat-rate	36%
Start and VOM costs	82%
Operating costs	24%

The largest number of updates were to the start and VOM costs, followed by heat-rate updates. Many of these heat-rate updates were designed to provide a more detailed representation of the heat-rate curve characteristics. Around a fourth of the plants had an update to their operational costs.

The largest value shift, and the most widespread shift in the provided technical and commercial data was due to the significant number of start-up cost updates. This may be primarily due to revisions of internal estimates when re-evaluating market offer drivers following the launch of I-SEM. In some cases, updates also reflect changes to participant exposure to these costs due to revised market-based contracts or service/maintenance contracts. Where changes were significant data providers were re-engaged with to request more information or a further review of the supplied data.

In aggregate the updates to technical and commercial characteristic data form a stronger representation of market behaviour since the I-SEM launch.

NOTE: Some of these model elements represent commercially sensitive information, these are strictly confidential and will not appear in the final publicly available validated model.

3.3 Storage and hydro

Storage is a key focus area across many markets due to increasing penetration of intermittent generation technologies (such as wind), and the gradual retirement of various flexible dispatchable thermal plant. The I-SEM is also encountering this trend, as can be seen with the inclusion of larger scale batteries in the future capacity auction outcomes.

The primary update on storage has been the addition of seven batteries to the model as shown in section 3.1. The addition of these batteries is based on the results of the latest capacity auction results and the DS3 frequency support outcomes which both project an increase in expected battery storage capacity. Each battery is represented by:

- Capacity
- Minimum stable level
- Minimum down time
- Charging efficiency
- Forced Outage Rates (FORs)
- Mean time to repair
- Energy storage capacity

As shown by the difference between the Capacity Auction outcomes and the DS3 frequency support auction outcomes, typically battery storage, hydro-based storage and hydro-generation facilities can play a number of different roles in the market. Each of these roles has an associated revenue stream and set of operational behaviours. The exact offer behaviour of these plant in practice will be shaped by:

- Provision of energy support. This means the energy storage will charge during periods where wholesale electricity prices are low (e.g. overnight) and will discharge when electricity prices are high (e.g. across peak time periods). The key revenues associated with this activity come from the arbitrage between the low energy prices at night, and the higher ones over peak time periods. The operational behaviours associated are a full charge across low priced periods and a full discharge across high priced periods.

- Storage providers may also receive revenues based on their role in providing energy support. In the event of an under-frequency event a partially charged storage facility may be capable of rapidly discharging to provide frequency support, or in the case of an over-frequency event a storage facility can charge and absorb some of the additional system generation. The operational behaviours associated with this may include charging and discharging within a more limited range of the total capacity so that some portion of the capacity is always available to respond to frequency events.

In practice most storage facilities will probably operate so as to receive revenues from both of these revenue streams. However, the aggregate operational behaviours associated will be partially determined by fundamental economics, and partially by any specific contracts or system requirements related to the two behaviours.

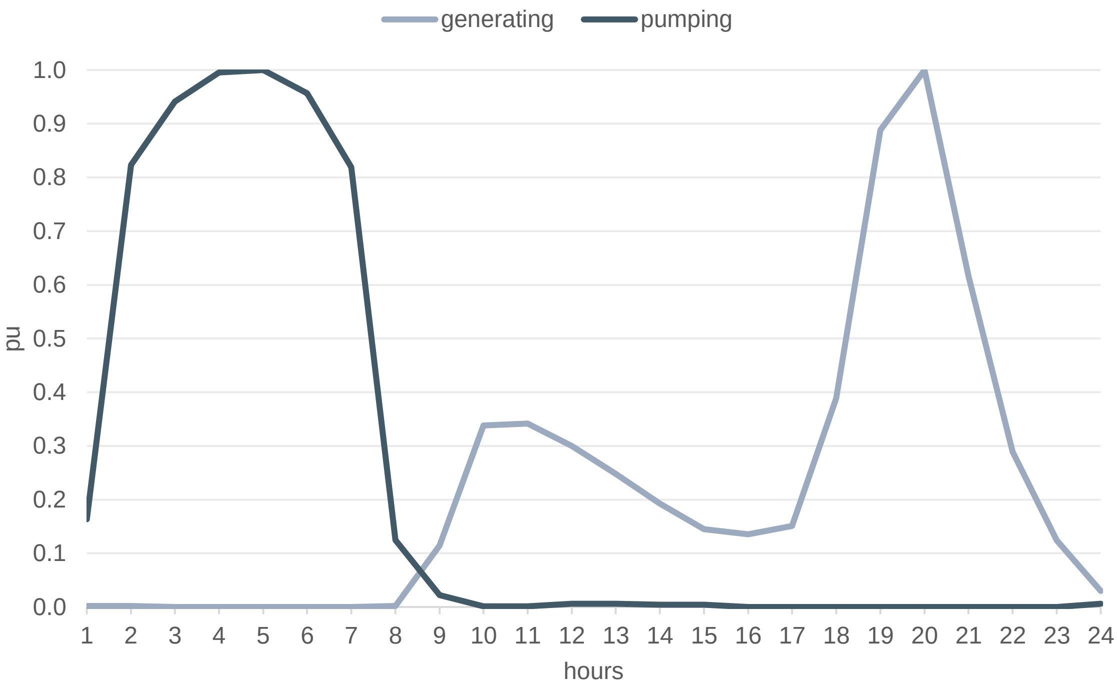
Since strong information in these areas is not yet available, the future installed batteries are assumed to primarily provide energy support, generating and discharging between wholesale energy arbitrage. This modelling approach will typically be correct for at least a large portion of the battery capacity and implies that the new storage is likely to follow a similar operating model to the existing pumped storage in the system. However, this approach can be less appropriate where storage is contracted or incentivised to provide very fast responses used to ensure grid stability. The modelling approach for storage technologies should continue to be monitored as more storage comes online.

Pumped storage and hydro modelling approach have not been changed since the last validation exercise except for the outage updated to reflect latest projections and some minor technical updates to a minority of plants based on the data collection exercise. This representation includes the following parameters:

- Capacity
- Max ramp up and ramp down
- TLAFs
- Planned outages
- FOR
- Mean time to repair
- Maximum and minimum energy storage volume

From the validation and engagement carried out there does not seem to be a change in market behaviour that would justify a change to these modelling parameters. Analysis of pumped storage dispatch indicates that it continues to be used primarily for energy support, pumping during off peak night periods and generating during peak periods.

Figure 3 Pumped storage hourly normalised generation and pumping historical pattern



Source: based on historical Oct 2018 – Sept 2019 data (hours based on market trading period)

The pattern of pumped storage use implies that the value accrued for pumped storage is primarily through time-based energy price arbitrage. This reinforces the hypothesis that the most appropriate representation for other storage (batteries) would be driven opportunities for energy price arbitrage.

3.4 Outages

The model parameters driving both planned and forced outages have been updated in the model. The approach used is described in the following sections.

Planned outages are generator and transmission outages which are typically for the purposes of equipment maintenance and upgrades. These are known about in advance but planning schedules for these outages tend to be less reliable for dates further into the future as the maintenance needs of units may change between now and that date. The representation of these outages in PLEXOS follows a scheduled outage plan, where the expected outages for each unit are manually input with specific associated dates. The use of this methodology allows the PLEXOS optimisation algorithm to identify times of future expected unavailability for certain plant and to predictably incorporate those expected outages when determining the least cost outcomes.

Forced outages are generator and transmission outages which are unexpected and unpredictable. They will typically occur due to a technical issue with a particular facility. These are difficult to predict both in terms of when they will occur, and how long the maintenance will take to get the unit back online. The model representation of these is based on a percentage probability of an outage occurring, and an expected time for the outage to persist for. The model algorithm then uses a random number generator to distribute these forced outages randomly across the modelling timeframe.

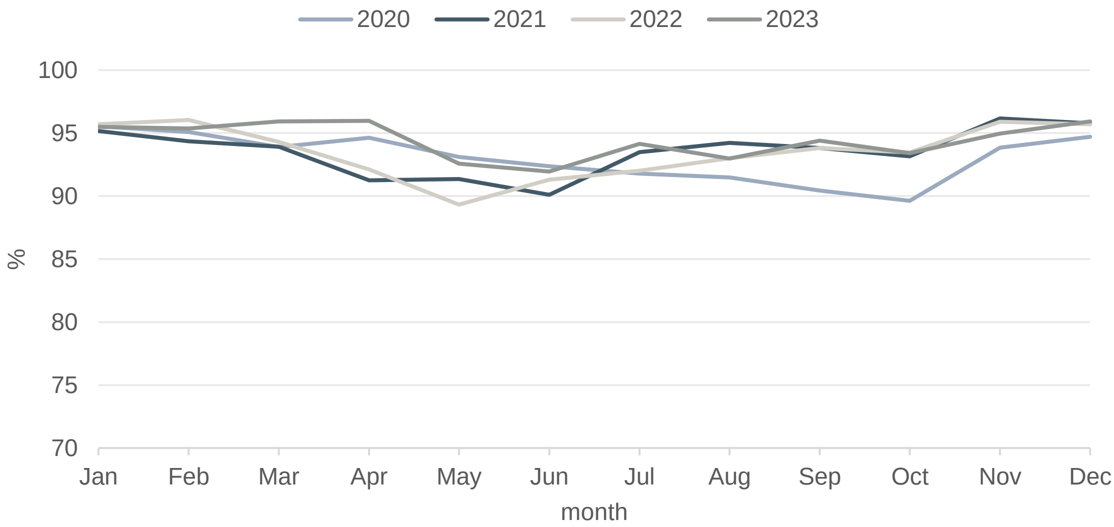
3.4.1 Planned

Planned outages to 2022 have been updated based on the published outage plan to 2022 provided by SEMO. These are outages specified per unit with a start and end time. For the period from 2023 to 2025 a theoretical outage plan has been constructed based on the published outage plan to 2022 and historical outage patterns. The process that was followed in creating representative annual outage schedule for the period 2023 to 2025 is described below:

- 2020 outage plan was used as the base year. 2020 is seen as the best representation to assume outages going forward as it is the closest in time and includes the most up to date knowledge.
- Plant level outages were analysed out to 2022 to identify outage patterns. This analysis was carried out by evaluating units in conjunction with similar units that were co-located and of the same type, age and company.
- Genuine outage patterns were identified and separated from one-off large outages. Larger outages were re-evaluated in groups of units against historical and future outage schedules. Where clear patterns could be identified they were included, either for the current plant or a plant of a similar type.
- Caution was used to ensure that outages between years were not artificially stacked during overlapping periods, something which in reality would be avoided.

The following figure provides an illustration of the monthly available capacity in years 2020 - 2023 with the inclusion of the updated outage plan. For comparison the average availability in the previously validated model in 2020 was 93.35% across all generating units compared to 93.04% in the current validation exercise. This is driven primarily by the latest published outage schedule from SEMO.

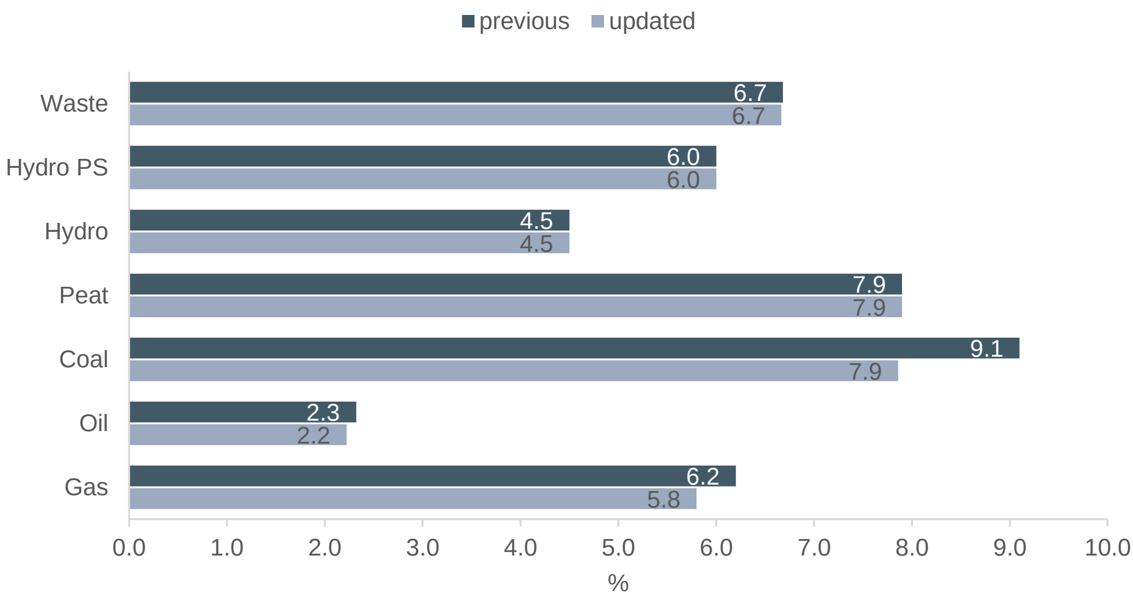
Figure 4 Available capacity 2020 - 2023



3.4.2 Forced

The forced outages were updated based on the technical data collection exercise directly sourcing information from generators. The validation and analysis of this data was combined with standard expected FOR from historical analysis. The figure below illustrates the average FOR per fuel category. Coal experienced the most substantial reduction in FOR due to the revision of the expected forced outage rate for two units.

Figure 5 Average FOR per fuel category



4 System data

System data updates have historically been performed using gross system inputs for electricity demand, embedded generation, and wind values.[5] This means that the entire physical system is represented in the PLEXOS model, rather than simply the components which are offered to specific markets. The aggregate system outputs from this approach will remain a strong representation of market results. This is because the supply and demand elements which are not explicitly offered to market will be netted off or entered as non-dispatchable facilities. Therefore, the physical realities of the markets should hold true. The remaining price and generation dispatch forming market elements will then predictably form the price in the same manner they would if only the elements which were directly offered into the DAM were used for the model.

This representation was chosen for a number of reasons:

- A comparison between the backcast results based on gross system inputs and those using the inputs given to EUPHEMIA for wind and demand gave very similar price and interconnector flow outcomes. This confirmed that gross system inputs were an appropriate representation of the system-based drivers for DAM market results.

- Available data sources are much more reliable and comprehensive on total demand. There are many years of gross demand data available which allows us to consider a range of historical profiles. At this stage there is only a single year of demand data cleared through the DAM. A single year of data will only reflect the market under a particular set of demand and weather conditions. It is less risky to use the gross data than to construct a set of theoretical historical market-cleared demand profiles based on a single year of data.

- Available data sources are much more reliable and comprehensive on total system wind. There are many years of gross wind generation data available, while only one year is available for wind cleared through the DAM. For example, the percentage split of wind which is offered into the market across that year is available. However, a single year of data will only reflect the market under a particular set of weather conditions. Additionally, there is no strong information on how that percentage split would have evolved over the previous years as installation capacity and locations evolved.

- Embedded generation profiles are available across historical years, alongside future projections developed by EirGrid. These are built to form part of the basis for wider market analysis on future expected generation and consumption trends by EirGrid. Consequently, they provide a better view of how growth in installed capacity of various technologies is likely to be accounted for in/outside of the markets.

- Future capacity and peak demand forecasts provided by the latest GCS (2019-28) reflect gross demand growth. Without several years of data, it is not

[5] In this instance gross system inputs are represented by whole-of-system actual data as developed from SCADA readings or directly supplied by EirGrid.

reasonable to infer a reliable relationship between these expected aggregate system projections and the representation of these system elements that can be expected as inputs to the DAM. This is particularly the case as different market segments are more/less likely to be offset against localised generation, as opposed to being brought to market. A new industrial plant may have a power-producing element to its industrial processes, whereas a new data-centre's full load is more likely to be directly incorporated into a market clearing mechanism.

- Future technology installation trend data which is available does not clearly differentiate between which capacity is likely to be cleared through the day ahead market as opposed to the installed capacity which may be incorporated into other categories including localised generation. There is insufficient market data at this stage to identify the key relationship between recently installed capacity and its likelihood to be offered into the day ahead market. This is particularly challenging in the area of wind where each site has its specific locational and capacity characteristics.

For these reasons the gross supply and demand methodology set out in previous validations was retained. Into the future, however, the development and maintenance of information sources which can clearly identify the evolving relationship between these gross demand, wind, and embedded generation numbers, and the offer/bid levels observed in the DAM is strongly recommended. Once three to five years' worth of data is collated comparing the outcomes then the RA's may be in a position to revise this methodology and move to one more directly related to market offers and bids.

4.1 Demand

Demand profiles used in the PLEXOS I-SEM model are based on hourly data. A range of annual historical hourly demand profiles are identified and compared to ensure they are a strong representation of overall system characteristics. Once these have been identified a set of forward-looking future expected hourly demand profiles are formed based on each one of the annual profiles. The future looking profiles are extrapolated based on future expected median annual peak and total demand (Total Electricity Requirement - TER) projections for each of the years in the forward-looking model horizon.

In this instance five profiles were used to provide five different annual demand profile samples, and these were then combined with future expected peak and total demand projections to construct forward-looking hourly profiles with the PLEXOS demand builder tool.

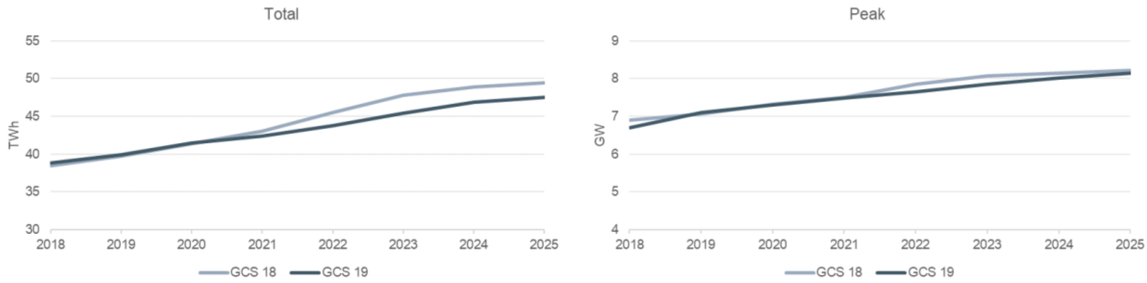
The model representation of demand and wind takes these five base year profiles and undertakes a series of simulations to construct a range of future expected dispatches and prices. This input validation continued the approach of previous validations correlating wind and demand. The mean of all runs was used as the core output from the range of scenarios. This approach adds robustness to the demand and wind modelling as it ensures the model is not restricted to the individualities of one year and also provides a good balance between running time and accurate results.

Changes to demand include:

- ❑ Update of annual peak and total demand projections to align with the latest GCS 2019 projections of the median scenario.
- ❑ Update of profiles used for hourly representation of demand to align with latest profiles available from 2014 – 2018.

The following figures illustrate the change in total demand and peak demand projections from GCS 2018 against GCS 2019. The latest GCS 2019 has lower total electricity demand and annual peak demand projections compared to GCS 2018 meaning that assuming similar capacity projections there is a higher capacity margin.

Figure 6 Annual total and peak demand projections



Source: GCS 2018 and 2019

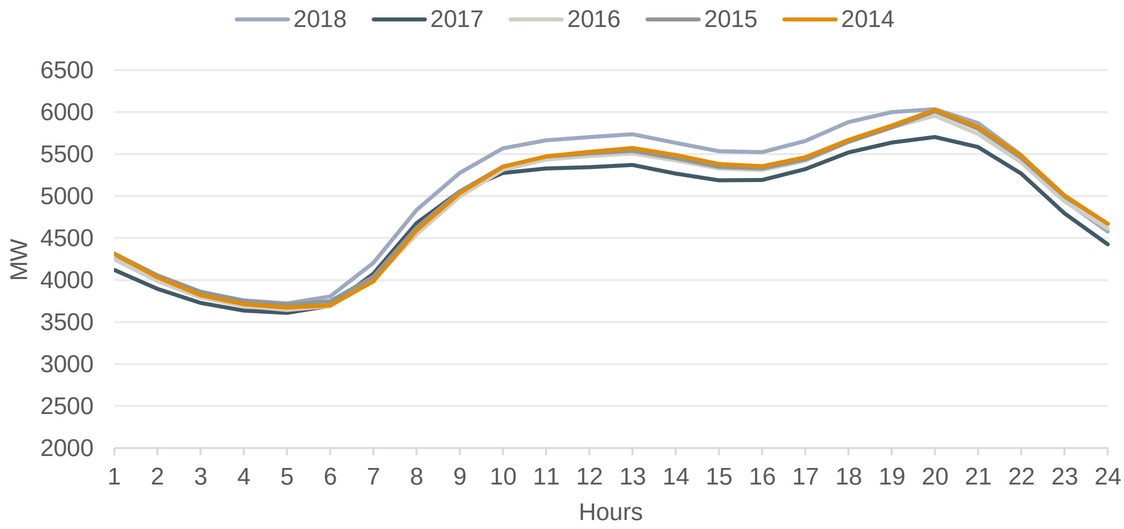
The other feature that was reviewed was the update of demand profiles to include the most recent hourly profiles. For this purpose, 2014 to 2018 demand hourly profiles gathered from the TSOs were used.

This decision was based on a comparison of the 2014-2018 hourly profiles against the existing historical profiles. It was deemed that the demand profiles for 2014 – 2018 formed a better basis for the model because:

- ❑ They are a more recent representation of demand profiles and more likely to represent current and future demand behaviour.
- ❑ No significant variations have been observed in any one year to signify it should be omitted. The profiles from 2014 to 2018 provide a good mix of variation between market states.

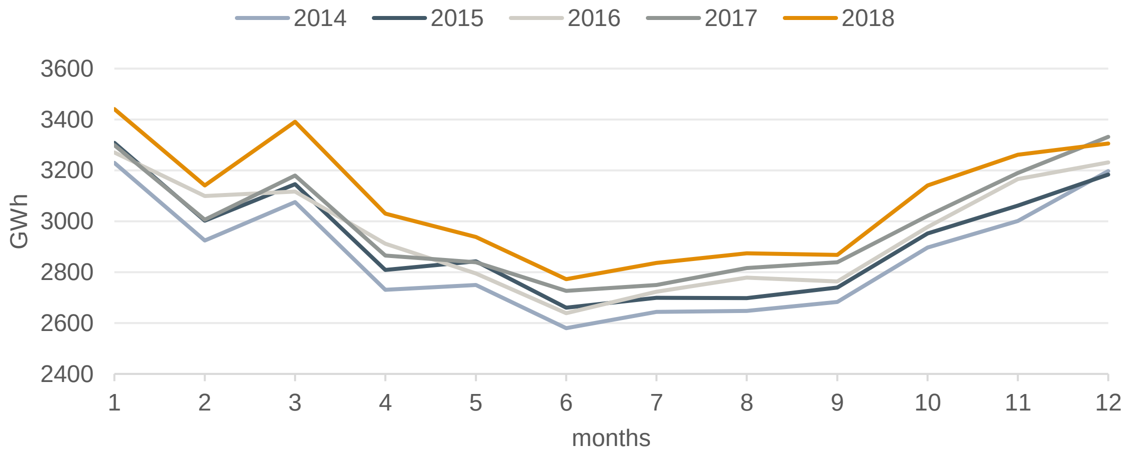
The PLEXOS demand builder is used to create five demand profiles, each one based on the actual demand profiles of 2014 to 2018 but scaled in a way to respect the annual expected total and peak demand out to 2025.

Figure 7 Representative average hourly demand profiles for March 2020



Five profiles based on 2014-2018 historical demand data

Figure 8 Total monthly demand 2014 - 2018



4.2 Wind

In a similar manner to demand, wind capacity factors are represented by hourly profiles. These profiles reflect the percentage of installed capacity expected to be dispatched at any one time. The percentage-based profiles are then applied to the total installed capacity linked to each profile.

Since no specific future trends in wind capacity factor were identified it was not necessary to build future expected hourly capacity factor profiles out to 2025. Instead the future expected growth is reflected by the installed capacity, while the capacity factor remains fixed. [6]

Wind, like demand, is represented by five base year profiles, each of which is correlated with the same base year demand profile. As a result, the market model inputs assume that the same factors which drive wind in the I-SEM also have an influence on demand in the I-SEM, and so wind and demand tend to be correlated in practice. This seems like a reasonable assumption given the strong impact of weather in forming both wind and demand drivers. As described above the model is run across this range of samples to produce a range of possible simulated outcomes. The mean of all runs is then used as a cumulative representative output. This approach delivers a reasonable balance between running times and modelling outputs.

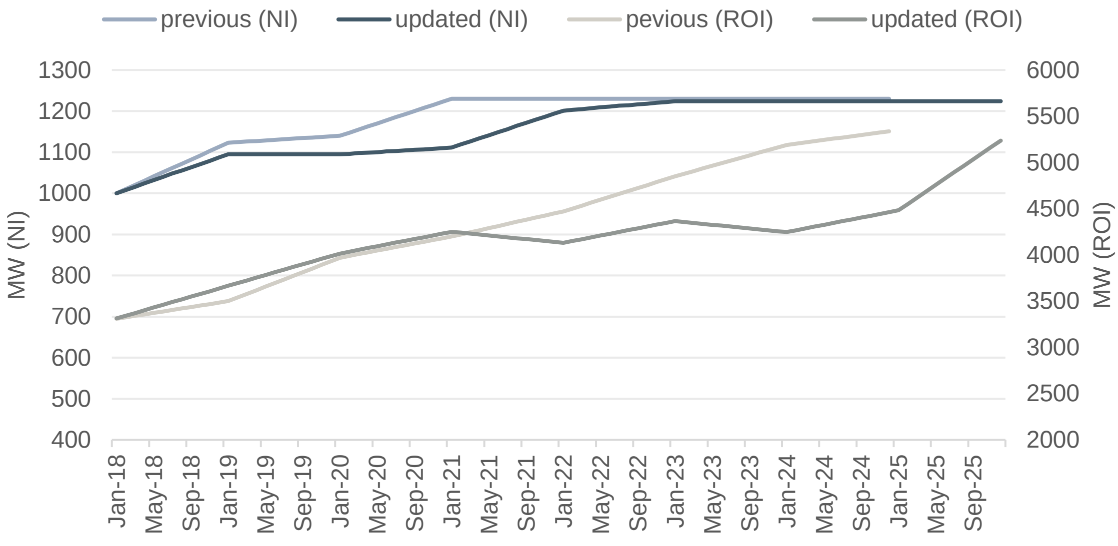
The updates to wind broadly mirror the updates undertaken for demand:

- The latest wind capacity projections to 2025 as per the most recent GCS. It is deemed that this data is the most accurate projection of wind capacities for the modelling horizon.
- More recent wind profiles including 2017 and 2018 are deemed a better representation of current and future wind behaviour as they capture a larger pool of windfarms across a larger geographical area.

The following figures illustrate the capacity growth comparison between the previous model and the updated model. Comparing the two, both in Northern Ireland (NI) and the Republic of Ireland (ROI) wind uptake is now expected to occur more slowly when compared to the previous projection. This means that less wind is available in certain years compared to the previous modelled values.

[6] In practice future capacity factors may change. This is due to two competing influences on realized wind-farm capacity factors. Technological changes and efficiencies may improve the ability of wind turbines to capture the available energy, and so to capture a higher percentage of the wind-farms installed capacity to generate. However, alongside this potential increase to capacity factor there is significant potential for decreases to realized capacity factor for new wind-farms. This is because typically the most promising wind flow sites are the sites which will be built on first. As wind-farms are increasingly placed on less promising sites the capacity factor for each of these new installations may decrease. It is assumed these two effects broadly offset one another and so assumed the capacity factor remains constant.

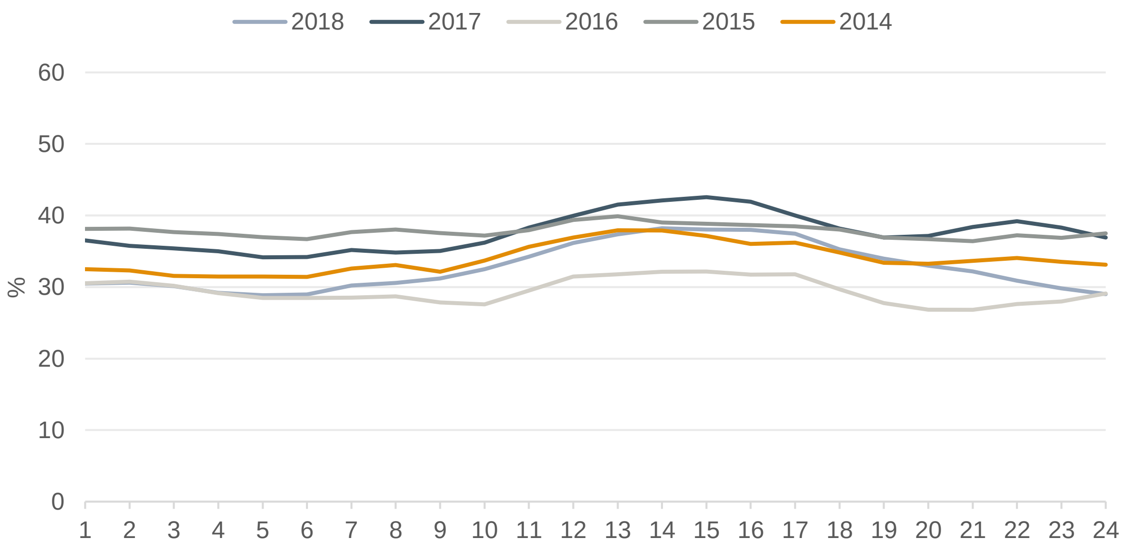
Figure 9 Wind capacity outlook



After analysing and testing wind capacity factors across historical years it appears that the years 2014 to 2018 provide a healthy variation between years with no particular extreme outliers. This means no years contain extended high wind or low wind periods that could distort model results. This also provides data which is easily correlated to the demand profile updates described above.

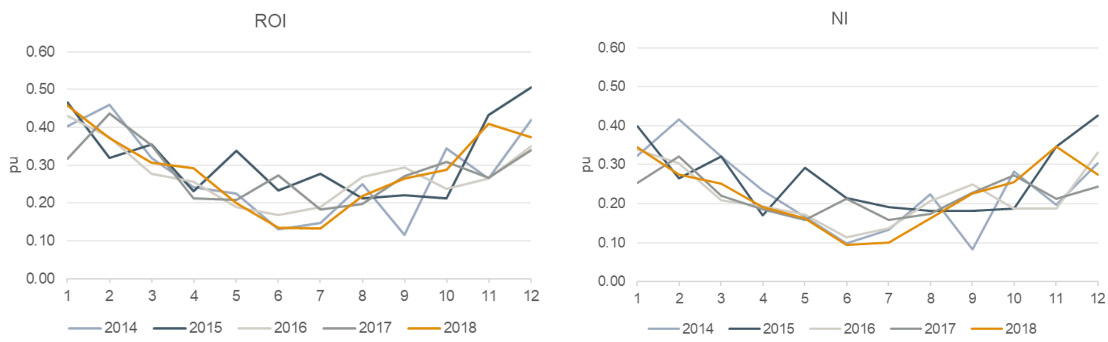
The data provided follows the same split as the previous model of wind being represented separately between NI and the ROI. Given the I-SEM clears as a single node market this would produce an adequate representation of wind.

Figure 10 Representative average hourly wind capacity factor for ROI in March 2020



Five profiles based on 2014-2018 historical demand data

Figure 11 Wind monthly average capacity factor profiles 2014-2018



SNSP Limits

SNSP limits in the market may restrict the percentage of demand which can be met by intermittent generation at a given point in time. This limit changes based on regulatory settings and has most recently been set at 70%.

The SNSP limits are applied to market in real-time. As a result, SNSP limits are unlikely to impact directly on market results, but an indirect impact may be seen at the gross input level (e.g. the gross wind profiles against gross demand). These are not the wind profiles which are offered to market, but since the basis of the PLEXOS model inputs is derived from the gross dispatched historical market outcome elements for both demand and supply then it is important to understand how the relationship between these core data-sources is likely to be impacted by SNSP.

To facilitate this a tool has been created that provides the option to calculate wind profiles, based on the correlation with demand profiles in a way that SNSP limits are respected. It manipulates the certain hours in the wind profile to ensure the intermittent generation quantity from wind never exceeds the limit set by SNSP. The tool is based on a monthly setting of the SNSP limits.

It was discovered through this process that the impact on modelling results is very limited curtailing an average of only 2.8% of total available wind energy per year per wind profile. Our initial view was that since it has a minimal impact and would ensure a stronger representation of the relationship between gross demand and gross wind dispatch, which would be netted off outside of the day-ahead market that these SNSP limits would be suitable for inclusion in the PLEXOS model.

However, following the December stakeholder workshop, a number of participants raised concerns that applying SNSP limits would unduly limit wind offers in a manner which had not been observed through the DAM offers. Their concerns were noted and consequently, it is recommended to exclude any explicit modelling of the SNSP limits at this time but continue to monitor for the purposes of model input validation. Also, it should continue to be observed whether or not there is any significant market impacts being introduced in the day ahead market due to these elements.

Areas for potential future improvements

At present offshore wind does not account for a substantial percentage of wind generation in either of these regions. However offshore wind capacities are projected to increase in later years, and if this trend continues to be shown it is recommended that the development of distinct profiles to represent onshore and offshore wind separately is considered. Typically, offshore wind tends to have higher capacity factors than the onshore equivalents. However, if such a split is going to be considered in the future then it is essential for the TSOs to begin collecting good data on the offshore wind profiles a number of years before it is introduced into the model.

4.3 DSUs

DSUs are Demand Side Units – these are price responsive consumers in the market. The majority of these price responsive units are willing to reduce their electricity demand in response to a particular price if they are cleared in the market. Some of these units represent facilities which have on-site generation capabilities as well. A portion of those with offsetting onsite generation units have negative bids reflecting their willingness to either reduce their generation dispatch in response to an appropriate market signal, or to increase their net demand through other means.

The modelling of DSUs involves segmenting the available capacity into a discrete number of price categories and using the price to represent their willingness to forgo electricity consumption for market-based remuneration. The analysis that underpinned the creation of the bands is based on existing market offer data. This modelling approach is similar to that in earlier models, however based on the available market data an approach was chosen which categorised DSUs into six units rather than the previous five. The latest market offer data indicated that it allowed us to provide a stronger representation of the DSU offers most likely to be cleared into the market. A key focus was ensuring smaller quantity bands were used for the lower priced DSUs, since these were the most likely to impact modelled market outcomes by being called upon. It was assumed that as the number of DSUs grew into the future that a similar proportion of the capacity would be attributable to each offer band. These bands and their projected growth are shown in Figure 12 below.

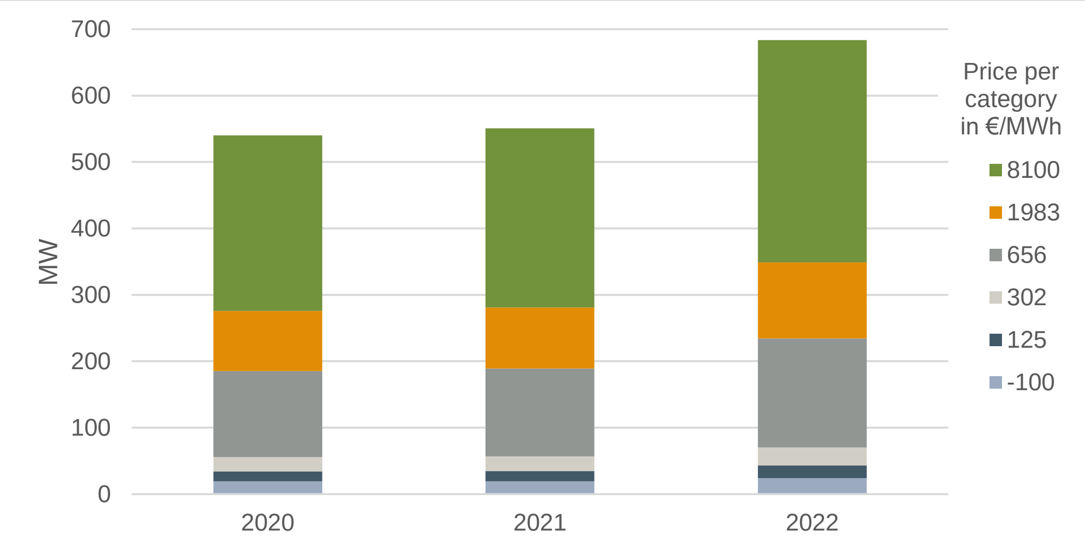
DSU modelling has been updated based on:

- ❑ The latest DSU capacity projections from GCS 2019.
- ❑ The installation dates of the latest T-4 2022-23 capacity auction outcomes.
- ❑ Observed offer data.

Notably a large proportion of DSU capacity is currently bid into the market with high minimum income conditions and would usually only be dispatched when the market is in extreme stress across a very small number of trading periods within a day. The resultant effective bid price for many of these units is higher than the price of €8,100/MWh that they are represented by here. However, since the €8,100/MWh price is not reached in any scenario there is little value in representing the granularity above this price.

Also, if there was a prolonged extreme market stress then these DSUs may be activated regularly in the market, and the minimum income requirement spread over higher trading period numbers. This would mean a lower effective bid price per hour. While this is currently unlikely based on market results to-date, the DSU structure should continue to be monitored as if these high priced DSUs begin to be dispatched in the market regularly then the pricing of these units should be reviewed, alongside the granularity of representation in the model.

Figure 12 DSU growth per category



4.4 Interconnectors

There are two interconnectors which are currently commissioned in the I-SEM. The Moyle interconnector connects NI to the north of GB's electricity market, while the East-West Interconnector (EWIC) connects the ROI to a more southerly point in GB's electricity market.

Greenlink is a planned interconnector between GB and Ireland. Although its connection date could fall within the modelling horizon for validation it is still subject to approval from CRU and Ofgem. Following discussion with the RAs it was therefore deemed out of scope for this validation exercise however will be monitored and considered in future validation exercises.

Moyle and EWIC have both a published rated capacity, and an allowable transfer limit. While the rated capacity is fixed, the allowable transfer may differ based on seasonal and environmental factors. While EWIC does not have seasonal capacity allowances, the Moyle interconnector has evolving specific firm contracted capacity limits for transfer from NI into GB. Each of these is identified for specific time-periods from November 2017 through until the full capacity is expected to be available in April 2022 onwards. Additionally, a day ahead process can allow nominated capacity to exceed these published limits on a day-to-day basis.

For the purposes of the forward-looking PLEXOS model the interconnectors are modelled in accordance with official published ratings as per the Moyle Interconnector Ltd Interconnector Capacity Calculation in July 2017.[7] This includes technical parameters, ramp rates and contracted capacity volumes. It is noted that Moyle has a varying limitation to its maximum capacity as illustrated in the table below. This follows the approach used in previously validated models.

Table 7 Moyle interconnector contracted capacities

Direction	Dates	Firm contracted capacity (MW)
Moyle - west to east	10 Nov 2017 - 30 Nov 2019	80
	1 Dec 2019 - 31 May 2020	307
	1 June 2020 - 31 Oct 2021	250
	1 Nov 2021 - 31 March 2022	160
	1 April 2022 onwards	500
Moyle - east to west	Months November - March	450
	Months April - October	410

Areas for potential improvements

There are observable differences over the historical time-period between these published flat capacity limits and the actual capacity limits seen in the market. Consequently, analysis was carried out to confirm whether or not the standardised capacity limits described above were a reasonable representation of the market. This analysis included comparing historical flows, day ahead forecasted transfer capacities and the firm contracted capacities since I-SEM's introduction.

It is noted that day ahead forecasted transfer capacities may vary in practice compared to the flat firm contracted capacities in Table 7 for Moyle. However, average flows tend to respect these limits. On average the annual physical outcomes should be a reasonable representation, but when broken down by month or day the peak flows may be limited in the model compared with what would be expected in the market. Unfortunately, there is insufficient data to reliably predict the times and profile of actual interconnector availability

[7] Moyle Interconnector Limited, Interconnector Capacity Calculation, July 2017. http://www.mutual-energy.com/wp-content/uploads/downloads/2018/01/170720-Moyle_Capacity_Calculation_July2017-approved.pdf

compared to these flat limits going forward.[8] This issue is worsened by the fact that the limits being calibrated change moderately often.

Given these difficulties, and despite the inherent limitations, the published firm capacity remains the most robust representation of interconnector limits currently available. Notably the interconnector capacity modelling has the potential to evolve into a better representation once more market data becomes available. Also, beyond 2022 these limits should no longer impact on modelled market results.

Interconnector outages are applied in the same way as the generation unit outages described in section 3.4. For forced outages the current forced outage rate is aligned to the SEM CRM Parameters Decision Paper from 2017.[9] This is expected to be reviewed as appropriate by the RAs as part of setting CRM Parameters for each auction round. No new interconnectors are introduced within the modelling horizon out to 2025, this is based on the latest projections, regulatory approvals and discussions with the TSOs and RAs.

4.5 TLAFs

TLAFs are used to represent the transmission loss factors applied to generation from different generation facilities when considering the proportion of that generation which is delivered to the markets. These are held as standard values each associated with a specific unit.

The TLAFs are published by EirGrid regularly and the modelled values have been updated to reflect the latest published 2019/20 approved values[10]. New plants that do not exist yet but are commissioned throughout the modelling horizon are assigned TLAFs from the existing data based on their location. The effect of the TLAF update on modelling results is minor, and these plants should have their TLAFs updated as new values for them are issued by EirGrid.

4.6 Embedded generation

Embedded generation represents non-dispatchable generation and some partially dispatchable generation whose input is fixed in advance; this may incorporate some small-scale wind.

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[8] As part of stakeholder feedback, a potential approach was suggested which would link interconnector availability to wind levels. However, given the large changes in Firm Contracted Capacity in Dec 2019 and again in June 2020 we did not feel sufficiently confident that historical analysis on this would provide useful information on the future relationships between capacity and wind to implement such an approach as part of this model validation.

[9] https://www.semcommittee.com/publication/publication-crm-parameters-decision 10 April 2017

[10] http://www.eirgridgroup.com/customer-and-industry/general-customer-information/tlafs/

Embedded generation has been updated with hourly profiles provided by EirGrid to 2024. These have been validated by comparison to technological growth trends and extended to 2025. In general, the updates in embedded generation are small in scale and do not have a significant effect on model outputs.

5 Commodities

Commodity price updates can result in large changes in price and dispatch dynamics. This is because the short-term volatility can drive a shift in the likely merit-order dispatch in electricity markets.

In practice model users are expected to update these values based on the most recent available information. All forward-looking analysis was performed using the set of values detailed in Table 8 below to retain a consistent outlook on the impact of different key changes to generation and system data.

5.1 Fuels

Fuel pricing can be input on a quarterly basis and should be updated to reflect the model user's best future expectation at the time of modelling.

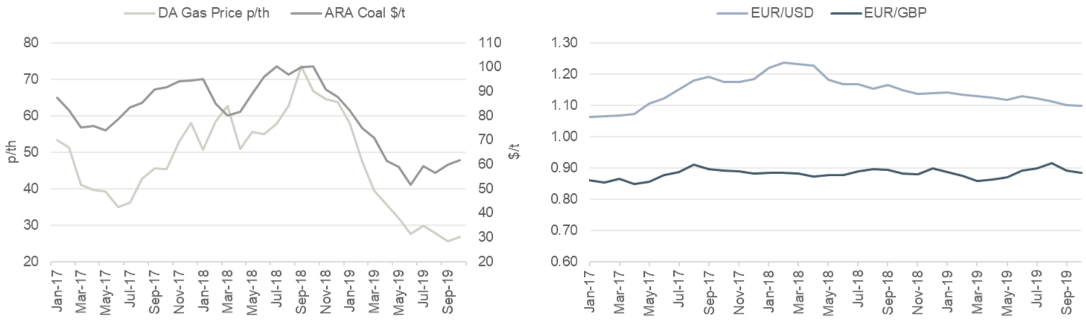
To test the sensitivity of model results to changes in fuel pricing, a version of the model has been created where commodity and exchange rates were kept at the values used for the 'Round 8 of Quarterly Directed Contracts' in September 2019. All comparisons between updates referenced including the waterfall chart (Figure 27) are based on these commodity assumptions also summarised in Table 8. This is only for indicative comparison purposes and to keep the commodity assumptions constant whilst carrying out other model updates. In the final model released to the RAs commodity pricing will be based on the latest fuel data as of 30 October 2019. As would be expected, any large shifts in short-term fuel data will have a significant impact on model price and dispatch outcomes.

Table 8 Commodity and exchange rate assumptions used as base for model updates (from Round 8 of Quarterly Directed Contracts)

	Q1 2020	Q2 2020	Q3 2020	Q4 2020
Coal ARA API2 $/t	62.40	64.38	66.50	68.70
Gas p/th	54.48	45.92	44.99	52.34
Gasoil $/t	539.43	536.96	538.67	537.99
LSFO $/t	363.93	366.43	369.28	365.09
Carbon €/t	28.57	28.57	28.57	28.57
EUR to USD	1.1202	1.1202	1.1202	1.1202
EUR to GBP	0.9235	0.92353	0.92353	0.92353

Modelling outputs are significantly impacted by any movement in the relative pricing of commodities, exchange rates and carbon. Historically commodity prices and exchange rates can vary significantly as can their interrelationships. Model users are expected to regularly update commodity and exchange rate assumptions before carrying out simulations. This is best practice and ensures that modelled outcomes capture the most recent market drivers.

Figure 13 Historical volatility of gas prices, coal prices and exchange rates



*Prices are nominal

5.2 Carbon

Carbon pricing captures the additional costs incurred by thermal-based electricity generation due to their carbon emissions. The costs associated with carbon emissions will differ across the regions which impact on the I-SEM. These are the Republic of Ireland, Northern Ireland and Great Britain. GB has a separate carbon price input in the model so that any changes in carbon price can immediately be incorporated into the aggregate price outcomes.

The carbon price applied to ROI and NI is the European Union Emissions Trading System (EU ETS). For GB the carbon price is made up of the EU ETS and the Carbon Price Support (CPS) as part of the UK government's policy to implement the Carbon Price Floor (CPF) to support the EU ETS.

The CPS top up of GB's carbon price as an addition to the EU ETS is defined by the 'carbon floor price target'. When the CPF was initially introduced in April 2013 at £16/ tCO2 it was intended to rise to £30/tCO_2 until 2020. However, in Budget 2014 a price freeze of £18/tCO_2 was introduced from 2016 to 2020 which was later extended to 2021 in Budget 2016 and reiterated in Budget 2018. GB carbon pricing is an area of uncertainty and Brexit outcomes may shape its future pricing.

GB, NI and ROI carbon pricing can have a significant impact on interconnector flows and DAM prices. The input sheet described in the following section allows for carbon pricing to be updated. Speculation on future carbon pricing is out of scope for this update. It is recommended that this area is monitored and updated accordingly based on latest evolvements before model runs.

5.3 Fuel adders

Fuel adders are used in the modelling environment to represent cost-elements which are outside of the base fuel costs. These may include transport costs, physical delivery premiums, transport and port costs, gas transport costs, gas network operator costs, delivery to site costs and other specific uplifts.

The fuel adders have also been updated to reflect recent changes in RA and participant estimation of incremental costs related to fuel procurement. Updates have been made to the 'Gas NI', 'Gasoil ROI' and 'LSFO ROI' fuel categories to reflect latest actual values. The changes are small and have a minor impact on model results.

5.4 Input sheet

To incorporate commodity inputs into the model a commodity input sheet has been prepared that takes as inputs the latest commodity price, carbon price projections and exchange rate assumptions. These are used to calculate the final price to be input into PLEXOS for each fuel category and puts these into a format suitable to be used as a model input. This is similar to input sheets used in previous years for this purpose.

Both the input sheet and the model (where applicable) have been updated to accommodate for the changes summarised in the following table.

Table 9 Commodity input sheet updates

Parameter	Update
Commodities	Updated with latest values
Fuel adders	Small updates (Gas NI, Gasoil ROI, LSFO ROI)
ROI short-term gas capacity	Updated from quarterly to monthly variation
Dublin Bay	Updated to reflect it is now purchasing short-term gas capacity (change effect from 26 Aug 2019)
Peat	Fuel option added for Peat plants (ability to separately enter for Lough Ree/ West Offaly and Edenderry)

As described in previous sections commodities have been updated to reflect latest data available. Some small changes to fuel adders are incorporated to reflect latest values to three of the fuel types.

The 'ROI Short-Term Gas Capacity' fuel type was updated from a quarterly to a monthly variation which provides a better representation of the variation observed in reality.

'Dublin Bay' has been updated to reflect that as of the 26th of August 2019 it is purchasing Short-Term Gas Capacity.

Fuel prices for all peat plants have been set up to allow for the introduction of a peat fuel price if needed. This was requested by the RAs as they have been informed that from the start of 2020 Lough Ree and West Offaly will have a change in their fuel contracting arrangements. Historically, peat generation at the two ESB peat plants were supported under the Public Service Obligation (PSO) scheme. As these plants move past the PSO peat supported period at the end of 2019, ESB will be going to market for new fuel sourcing arrangements, therefore it is reasonable to model these with an explicit fuel price. The impact of this change may mean these peat plants will operate less as baseload plants from this date onwards.

6 Model parameters and sensitivities

6.1 Daily market optimisation parameters

The PLEXOS model solves over the modelled horizon (e.g. 1-5 years) by discretising the problem into smaller interlinked sub-problems. For modelling the SEM, the sub-problem length is typically a day, with a designated start-time, and will include a few additional hours look-ahead. The start-time is the time of day where each sub-problem starts, while the look-ahead represents that market participants have some expectations (an imperfect foresight) of what is likely to happen in the market dispatch and pricing outcomes beyond the end of the day.

Start-time

Historically the SEM PLEXOS model has used a start-time for each day of 6am which aligns with market solution outcomes prior to the launch of the I-SEM. The market start-time for the EUPHEMIA algorithm used to optimise the day ahead market scheduled outcomes is 11pm.

Changing the model start-time from 6am until 11pm was tested. This resulted in small changes to the aggregate solution, however the source of those changes was evident and when tested as part of the backcast methodology it was discovered that this later start-time represents a better representation of the day ahead market behaviours.

The source of these changes relates to how the optimisation horizon is separated into different problems. PLEXOS will separate the annual problem into different stepwise segments and each of these segments will be formulated and solved independently, using the end-state parameters from the previous solve as the start-state parameters of the solution for the next problem set-up. Effectively PLEXOS is comprised of a chain of interconnected problems, each of which is optimised independently. When the start-state for the model is set at 6am this means that the end-state of each of these interconnected problems is just prior to the morning peak. With a 6-hour look-ahead the optimisation will also cover the morning up until 12pm. The start-state for the next day coincides with the morning peak. This would produce higher unit commitment at the end-state from the previous model solve as it anticipates high value across the day.

In comparison an 11pm start-state means that the end-state of the interconnected problems occurs after the evening peak, including 6 hours look-ahead the optimisation will cover the morning up until 5am. The start of the next problem begins during low demand periods. This will result in lower unit commitment at the end of the daily modelled horizon, as it anticipates low return on generation which is kept online overnight.

In both options the existing unit commitments and generation levels will be shaped by the trajectory at the time when the market solution changes, and neither is fully neutral as a solution. However, the 11pm market start-state induces more flexible solutions and will mean that the start-state of the market optimisation will be less strongly influenced by the optimisation problem outcomes from the previous day.

This has advantages and disadvantages:

- this means that the PLEXOS model will more closely resemble the EUPHEMIA model which does not directly consider prior knowledge of generator positions for each day.
- this also means a reduction in the quality of representing traded off-peak strategic offering behaviours on units which wish to remain dispatched overnight so as to avoid incurring start-up costs for the morning peak.

The former seems a reasonable advantage given the PLEXOS market model outcomes more closely resemble the historical behaviours. However, the latter implies potential value in exploring a range of different look-ahead scenarios both with a 6am start-time and a 11pm start-time to better understand the impact of these changes. The particular focus of this exploration was how well they relate to the historical backcast time period in order to discover the balance of settings that is the most appropriate fit for real market behaviours.

Look-ahead duration

Like the start-time of the model, the look-ahead functionality in PLEXOS is particularly significant to the end-state and start-state of the interconnected modelled problems. This represents how many hours are added to the end of the model horizon to take into account the perceived opportunities and forward-looking trading behaviours across the following hours. The actual solutions across this look-ahead time period are then discarded, but they can have a significant influence on how well dispatch decisions represent trading behaviours over key time periods.

The current look-ahead setting was 6 hours – this meant that from a 6am model start/finish time, the model would optimise over the next 30 hours through until midday the following day. The final 6 hours of solution data were then discarded, and the model state at 6am the following day was used as the initial conditions to set up the next 30-hour model timeframe.

This look-ahead functionality primarily represents the way traders are thinking ahead when they are deciding what sets of bids and offers they want to show the market clearing algorithm. It is not intended to strengthen the optimisation algorithm, but instead to strengthen how well the model solution replicates the decisions being made by the aggregate group of traders themselves.

For example, a trader with a high start cost may decide to offer a price lower than its marginal cost on overnight generation so that the plant will remain online through until the morning peak the next day and so avoid incurring those expensive start costs.

As identified in the 2018 SEM PLEXOS Validation Report this limited explicit look-ahead is a fairly strong compromise. While the EUPHEMIA model has no explicit look-ahead function, traders have the ability to look into the future as far as they want but with increasingly imperfect foresight.

Given the range of trading behaviours since the launch of the I-SEM, the efficacy of the PLEXOS model in replicating market outcomes across a range of different look-ahead settings was evaluated.

Table 10 Impact of changes to look-ahead (base 6-hour look-ahead 11pm start-time)

Look-ahead (hours)	Price change (€)	Average monthly interconnector flow to GB change GWh	Average monthly interconnector flow from GB error GWh
0	- €0.55	+8	+2
2	- €0.12	-3	+4
4	- €0.01	+1	+3
6	Base	Base	Base
8	- €0.08	+3	-2
10	- €0.23	+32	-33

The most robust look-ahead model setting is to retain the 6-hour look-ahead because there exist only small differences between the solution outcomes across the range of possible lookaheads. A trader deciding their bids and offers for an 11pm market solve would have in mind the set of bids and offers which would best ensure a physical dispatch overnight which prepares them for the start of the morning peak.

Interestingly the move from a 6am market start-time to an 11pm market start-time means the look-ahead time has a much lower impact on the aggregate market outcomes as can be seen in the table above. As a comparison, for the 11pm start-time having no look-ahead sees prices reduce by €0.55 on average, whereas for the 6am start-time the same change results in a price increase of €1.43 on average.

Exploring the unit-level data for a range of units across the market indicates that a 6 hour look-ahead has the most reliable trade-off between appropriate overnight trader behaviour looking to induce specific unit commitment outcomes, while also enabling mid-merit and peaker units with lower start costs to identify time periods where they may wish to trade so as to not be dispatched in the market.

6.2 PLEXOS version

While the current RA I-SEM PLEXOS model uses PLEXOS version 7.3, there have been a number of updates to the PLEXOS software, and PLEXOS version 8.1 is now the most recent version. It is recommended the RA's PLEXOS model is moved to the new version.

Minor variations were observed in solution results for a specific run due to the following model updates:

- A change in the random number generator changed outage patterns. (Changed as of PLEXOS v7.5)
- Solver upgrades can cause different outage patterns. (Changed as of PLEXOS v8.0)

Some users have noted an increase in run-times compared to version 7.3, however any run-time changes will be heavily dependent on the hardware used.

A table of the aggregate solution changes is shown below.

Table 11 PLEXOS version aggregate solution changes

	PLEXOS 7.3	PLEXOS 8.1	Total change	% change
Annual average prices	€47.27	€47.20	-€0.07	-0.2%
Annual average gas generation	22943 GWh	22886 GWh	-57 GWh	-0.3%
Annual average GB interconnector bid dispatch	9044 GWh	9089 GWh	44 GWh	0.5%

6.3 Uplift algorithms

The model uplift algorithm is a way of ensuring the market pricing in the I-SEM PLEXOS models is a closer representation of how traders are incentivised to offer into the market. The way uplift is approached in market modelling for the SEM and I-SEM is partially due to the history of the SEM market, and partially due to its method of representing behaviours otherwise unaccounted for in a marginal cost-based system.

The SEM worked on the basis of short run marginal pricing with an added uplift component. This means that the incremental generation cost formed the core price signal (what does the next unit of dispatch cost for a particular plant), while the uplift would add additional value to that marginal price to represent generators recovering their start-up and no-load costs. When the shadow price is not sufficient to cover the costs for plant which are required in the market then an uplift algorithm will generate an adder to the electricity price and increase delivered electricity prices to cover these costs. In some markets, such as the SEM this was explicitly considered by market operators using algorithms to identify the required uplift in each hour. Programs like PLEXOS can replicate a range of these algorithms.

In the I-SEM arrangements there is no explicit uplift added to shadow prices, but the onus instead rests on the generators to form their commercial offers such that they can recover start-up and no-load costs in addition to incremental generation costs. Therefore, these elements are incorporated in the market offers, rather than addressed as a separate component.

One of the market mechanisms through which generators can signal this willingness to run only at prices which allow them to recover these costs is the minimum income signal which can form part of the complex bid and offer types in the market. These would represent a value that would incorporate both these start costs and their expected marginal generation costs if they were dispatched into the market.

Under the backcast analysis it is described how closely uplift mechanisms appear to replicate these minimum income conditions across a range of generation units.

6.3.1 In-built uplift algorithm vs customised generator mark-ups or algorithm

The 2019-2023 I-SEM Validated PLEXOS Model includes uplift, which is not a direct reflection of market price formation for the I-SEM as uplift is not explicitly considered in the EUPHEMIA market settlement algorithm. In PLEXOS modelling uplift reflects that generators will seek to recover the start-up and no-load costs from the market. Therefore, bids into the I-SEM can be expected to be structured so as to cover these costs, and the prices delivered by the market will continue to incorporate these components in some form.

The key alternative to any standardised uplift algorithm applied across the entire model is to individually apply the uplift components observed for each generator in their bid and offer behaviour to the market. This approach may improve how well the model outcomes reflect the market over a historical time period, but at the expense of a maintainable and appropriate forward-looking perspective.

The second alternative is to customise an uplift algorithm for the PLEXOS model based on observed I-SEM trading behaviours. This approach may be appropriate once sufficient market data is available across a range of different market conditions.

These approaches are limited as bidding behaviours of past traders are not necessarily the best representation of future expected bidding behaviours. They are therefore unlikely to be a strong representation across the five-year forward-looking timeframe. This is particularly true for new generation plant where the trading behaviours are unknown.

Likewise, at present there is very limited historical data on which to base either an individualised estimation, or from which to develop a market-specific uplift algorithm.

This is because trading behaviours in a steady state market will vary significantly by month based on expected demand, wind and fuel prices. A monthly level is the highest level of discretisation at which the analysis on which to base such an algorithm, could be reasonably undertaken. For more mature markets, a weekly discretisation would be more suitable.

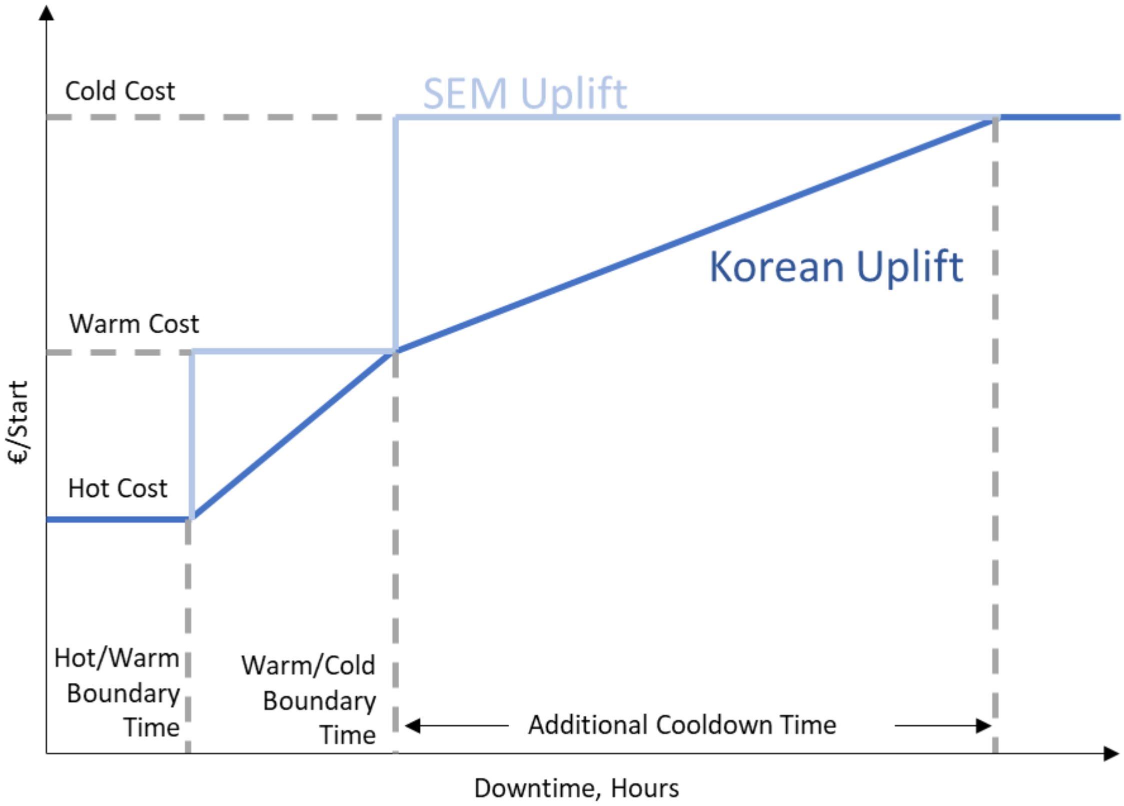
Moreover, within the month there will be significant and notable differences between weekends and weekdays, between peak and off-peak hours and based on expectations of demand and wind as formed by the weather. This means that the single year of trading data from the I-SEM effectively gives us a sample size of ~21 weekdays for each trading period depending on the month and ~10 weekend days for each hour depending on the month. All of these samples represent how traders traded in a single year's worth of underlying market conditions, and while they were encountering each month-by-month set of weather and demand patterns for the first time since I-SEM launch. It is recommended that the customised algorithm option be re-evaluated once more extensive market data is available.

6.3.2 Korean uplift vs SEM uplift

The two pre-programmed uplift algorithms available in the PLEXOS model are the "Korean Uplift" algorithm and the "SEM Uplift" algorithm. Each of these will be briefly described before discussing how well they represent price outcomes seen in the I-SEM to-date.

The Korean uplift algorithm as inputted into PLEXOS mimics a cost-based pool and uses a piece-wise linear function to represent start costs from each of the three possible start states (hot, warm, cold). In contrast the SEM algorithm represents the uplift mechanism which was used as part of the SEM market and it uses a stepwise function to represent start costs from each of the three possible start states (hot, warm, cold). An example is shown on the diagram below.

Figure 14 Start costs in SEM uplift algorithm, vs Korean uplift algorithm



Each algorithm has certain benefits and drawbacks:

- The Korean uplift algorithm is a better representation of the operational realities of thermal plant cooling. A plant doesn't instantly change from being in a hot state to a warm state because it reaches a particular set boundary. In practice the cooling process is gradual and so at least some portion of the accrued costs will be linearly related to that cooling trajectory.

- The SEM uplift reflects how generators were accustomed to receiving their uplift reimbursement and so the trading behaviours may reflect an expectation of recovering costs in this way. Typically, internal cost-estimation methodologies will take time to evolve even after a large market design shift.

- Market bids and offers can be expected to reflect a greater level of risk-averseness than is currently accounted for in the Korean uplift algorithm. This represents their internal hedging against the risk that their plant may be committed to the market for only a short period of time which leaves them unable to fully recover their start costs. One method used in the market bids presented to market to protect against this risk will be the minimum income requirement component of complex bids.

- Market bids and offers can be expected to reflect higher prices than simple uplift-based cost recovery mechanisms may account for when the demand response is sufficiently inelastic for certain portions of the electricity demand curve. Typically, generators are incentivised to price their bids and offers for the highest price that they believe the market is willing to pay to dispatch their units at. In portions of the supply curve where demand is inelastic and there are limited alternative generation suppliers who are able to meet that market need, then suppliers are incentivised to incorporate scarcity rents into the offer and bid pricing.

Ultimately the mechanisms used to incorporate any uplift to underlying cost drivers in the I-SEM will be down to the trader's discretion and will be done the day before. This means they may reflect the risk of starting a plant from multiple possible heat states. Thus, the smoothing introduced by the Korean uplift algorithm may well be a better representation of cost drivers in the long term.

Based on the assessment of price, interconnector and generation outcomes, the aggregate difference between the Korean uplift algorithm and SEM algorithm is minimal (the SEM produces prices €0.06 lower than the Korean). The Korean algorithm is a slightly better representation of the prices seen so far since the launch of I-SEM. This is primarily due to a slightly better representation of the shape of prices – peak prices are more appropriately captured in comparison to real market outcomes.

For these reasons it is recommended to retain the Korean uplift algorithm unless there is sufficient evidence from market outcomes that the SEM algorithm or a custom uplift algorithm would result in a better representation of the market.

6.4 Scarcity pricing

Scarcity rents are more likely to eventuate in the I-SEM (unlike the SEM) when the supply-demand balance is tight since generators are not constrained to bidding based directly on generation costs.

Scarcity pricing is not explicitly included in this I-SEM validated model. This is primarily because so far only a single year of market data is available, which makes it difficult to separate behaviours responding to unique annual characteristics from behaviours which will regularly recur in the market. It is recommended that evidence for scarcity rentals continues to be monitored across future backcasts to re-evaluate the usefulness of including scarcity rentals in the PLEXOS model.

As described in section 7.2.2 below, if there are scarcity rents being commanded in the market they are unlikely to be solely related to the total supply-demand capacity margin. However, they may be driven by scarcity in specific subsets of the supply-demand curve, for example when there is high wind and demand volatility but only a few units already committed to generate. Across the 2018-2019 I-SEM market period there was almost no evidence to suggest scarcity rentals in the market across winter months, while in summer months there was some indication that significant scarcity rentals may be entering the market on very low wind generation or high wind volatility days. A single year of data is insufficient to confirm whether these outcomes are likely to continue to be observed.

6.5 MIP vs RR

MIP (Mixed-Integer Programming) and Rounded Relaxation (RR) are two different methods for approaching the classic unit-commitment problem which underpins power-sector modelling. The unit commitment problem arises because power plant units are typically either in an online or offline mode. An electricity system pricing, scheduling and dispatching model such as PLEXOS will need to reflect the difference between these states in order to provide an accurate representation of the real system dispatches.

- **Online** – when a generation unit is in an online state then they are able to be dispatched across a range of different generation levels. However, for many units they will often have a required minimum stable loading while they are in an online state. This can mean that higher priced generation is dispatched rather than lower priced alternatives in a given hour so as to ensure the minimum stable generation requirements for a plant are continuously met. Thus, keeping a plant online may result in a more expensive market solution than switching the plant off and then back on again.

- **Offline** – when a generation unit is in an offline state then they are can only be dispatched by incurring start costs associated with switching on. Some units may have a minimum amount of offline time after being shut off. Units may also have a minimum amount of online time when switched on. There may also be a time cost as some plant will have a long start period due to ramping constraints. Thus, switching a plant off and then back on again may result in a more expensive market solution than leaving a plant online.

Unit-commitment optimization methods are designed to evaluate these potential costs so as to determine the state of each unit in each hour based on minimising the over-all system costs for each day while respecting the operational constraints on the unit.

Since there are only two possible discrete states for each plant this is a *non-linear* system element. Optimizing non-linear problems can be problematic, this is primarily due to significantly increased computing times for each integer variable in the system. PLEXOS offers three standard options for optimising unit commitment:

1. **Linear Relaxation.** This allows the non-linear dispatch to be converted to a linear problem. While this has rapid solve-times it also simplifies the system to allow all units to be partially online rather than simply in an online or offline

state. Typically, this results in less realistic dispatch solutions and lower prices than what will be seen in the real market.

2. **Rounded Relaxation**. This method performs an initial solve based on a linear relaxation, then determines the online/offline state of each unit based on whether their unit commitment dispatched in the linear solution meets a certain threshold. For example, if a unit is 70% online and the threshold is 60% then the solution would round this up to dispatch this unit as online. Whereas another unit which is only 50% online would be rounded down so it was offline. The unit commitment is significantly better than linear relaxation alone but may result in unit-commitment outcomes that are not fully optimised. The self-tuning feature in PLEXOS improves the solution quality by iteratively testing out the solution with a set of different commitment thresholds (e.g. 10%, 40%, 70%, 90%) then selects the least-cost system solution.

3. **Mixed Integer Programming**. This is an algorithm which will determine the optimal least-cost unit commitment decision. Typically, this produces lower-cost solutions for the market, but takes significantly longer to run. Additionally, there can be solution stability issues where there are several different unit commitment outcomes which produce the same over-all cost of supply for the market. In these circumstances then small differences in solution inputs may also result in significant changes to the portfolio of units which are committed to market over a given time-period.[11]

It is recommended that the RAs continue to use RR, as in previous models. This currently represents a reasonable trade-off between solution accuracy and computational time. It is further recommended that RR self-tune settings remain at 0.2 self-tune increment with a minimum threshold set to 0.1 and a maximum threshold set to 0.9. Changes to the self-tuning settings did not result in significant solution or run-time improvements. However, it is also recommended to continue reviewing and considering the option of using MIP in future market models.

Typically, if unit-based behaviours can be appropriately replicated by an RR approach then the simpler approach can provide increased visibility of aggregate market drivers as the market matures. If RR algorithms are unable to replicate the unit-based behaviours appropriately across the market, then MIP can provide additional insight. It is important to ensure that additional complexity is only added into the modelling methodologies when it appropriately reflects the real market complexity. This is best assessed once a market has reached maturity.

[11] This can significantly impact the quality of unit-based dispatch outcomes from the market model. When integer constraints were introduced to model interconnector states in the NZ market this problem created significant oscillations in scheduling, pricing and dispatch outcomes and was subsequently revised.
See discussion of wealth transfers as MIP solutions approach optimality in Sioshansi R, O'Neill R & Oren S S, "Economic Consequences of Alternative Solution Methods for Centralized Unit Commitment in Day-Ahead Electricity Markets" *IEEE Transactions on Power Systems*, May 2008, Vol. 23, No. 2, pg 344-352. Note: Despite the similar names, the other methodology used for comparison in this paper is **not** Rounded Relaxation.

The use of Linear Relaxation is not recommended as it cannot appropriately reflect the unit-commitment costs which are present in the I-SEM.

When evaluating the trade-offs between MIP and RR the solution outcomes were evaluated against actual I-SEM market results as part of the backcast. For further analysis on this see section 8.4.

Overall, it was found the MIP option increased annual average prices across the 2020 year by €0.27 and increased runtimes by between 7-20 times the RR runtimes.[12] Since longer run-times of this scale have the potential to adversely impact the delivery of regular analysis as part of regulatory process, this was deemed as unsuitable.

However, the calibration against real I-SEM data indicated that MIP was able to deliver a better replication of some market conditions. This was particularly seen in the summer months, while the winter months were more closely replicated by RR in most months. Thus, it is recommended that further analysis is undertaken on the impact of model simplification options on solution quality. Testing of these options was out of scope for the current process due to time constraints, however this is recommended for consideration in future validation and backcast exercises.

The core options for reducing this run-time are identified in the NERA Validation Report for I-SEM PLEXOS Model, 2018-2023. These include:

- Increasing the Relative Gap - this is the stopping point at which the MIP solution is considered a sufficiently high-quality solution to be acceptable when compared to the constrained linear version of the same problem.[13]
- Reducing the number of samples of load, wind and forced outages - this may significantly reduce the robustness of solutions to a range of future expected outcomes as it means that quality of results is very dependent on which sample (or set of samples) is chosen as representative.
- Representing the start-state of a plant by a single start state, rather than three – the current representation allows for three start states for generating units (hot, warm and cold). This improves the quality of the information about each unit in the model but may increase run-time.

6.6 Price cap and floor

Cap and floor levels have not changed and are maintained at €3000/MWh and -€500/MWh.

[12] The Baringa Model Validation Information Paper (2018-2019) reported an increase of 100x RR runtimes. This increase was not replicated in the results of this validation yet this indicates that much higher runtimes are a risk. Runtimes can also be impacted on the maximum allowable time for a sufficiently optimal MIP solution to be found. If this cannot be found in the designated time then PLEXOS will instead seek an acceptable RR outcome.

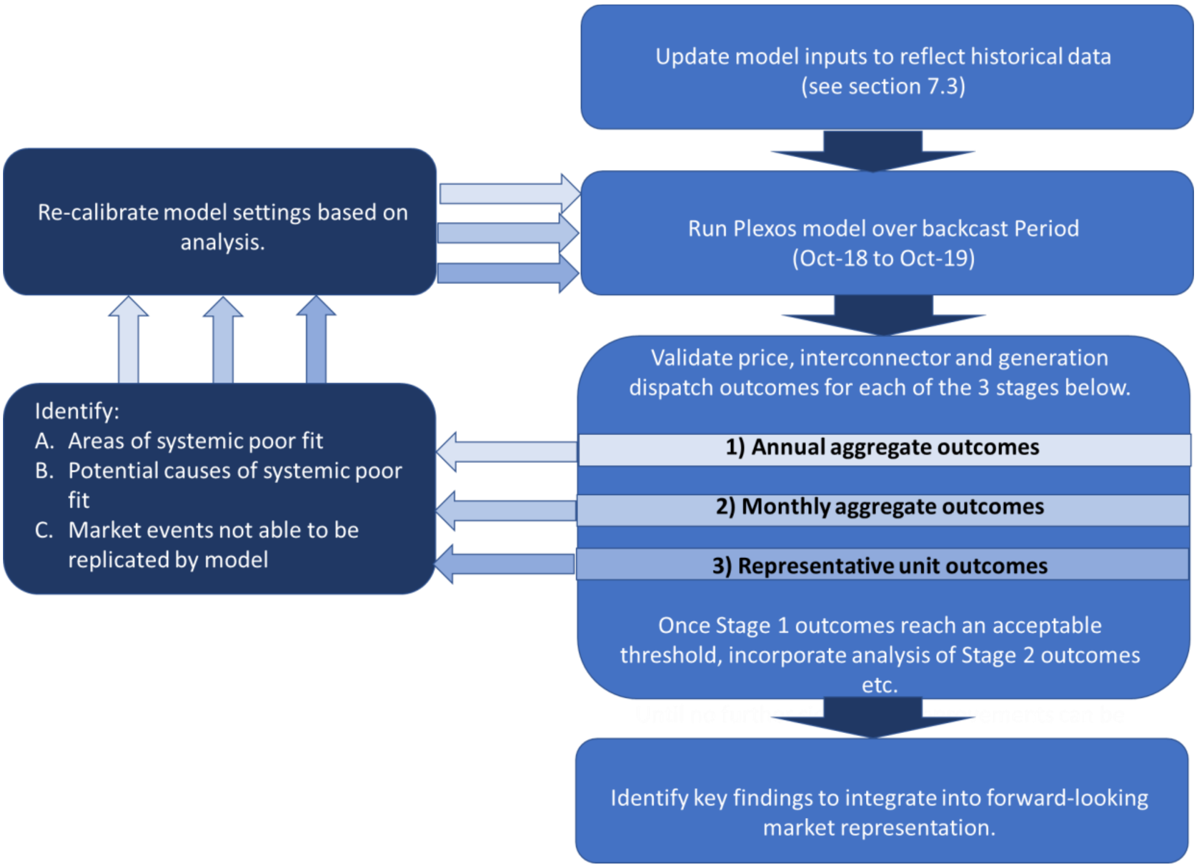
[13] The value changes resulting from different relative gap settings was not assessed as part of this validation. It is recommended that these options be further assessed in the future.

7 Initial backcast

7.1 Methodology

The backcast methodology which was used for this exercise is described in the following diagram.

Figure 15 Backcast methodology



7.2 Observations on market behaviours

With the launch of the I-SEM, there is a significant shift in the available information for market analysis. The aggregate outcomes should remain broadly similar since both the model and market will continue to be driven by fundamental generation cost, and demand economics. However the actual formation of bids and offers from an individual participant will be based more directly on how that participant's views of these fundamental drivers have shifted over time, how other participant's views of these fundamental drivers have shifted over time, and how these are woven into the bilateral arrangements they have in place to respond to these drivers.

7.2.1 Supply and demand – DAM vs gross actual

At this stage, there is only a year of DAM supply and demand data. The DAM data will differ from the historical gross system supply and demand for a number of reasons.[14]

- At the time the DAM clears the expected demand and wind offers are based on the forecast generation and expected wind.
- Not all energy generated and consumed will clear through the DAM.

In this section firstly the scheduled (DAM) and gross actual (EirGrid) wind and demand profile inputs are compared to see whether there is sufficient information to predict forward-looking DAM inputs based on their relationship to historical actual generation/demand values. Secondly this section contains an overview of the differences between backcast outcomes using scheduled (DAM) and actual (EirGrid) wind and demand profile inputs to the PLEXOS model.

Scheduled (DAM) inputs vs gross actual (EirGrid) inputs

The analysis of wind and demand inputs confirmed that the predictive relationship between scheduled (DAM) inputs and actual (EirGrid) inputs is not sufficiently robust to construct future expected DAM inputs based on historical observed bid patterns and forecast demand and wind levels.

For the purposes of validating whether or not the forward-looking market model represents the DAM appropriately, using DAM data presents some difficulties. As there is only a single year of DAM data, there is insufficient information on historical trends to form a sound basis from which to create forward-looking demand and wind profiles.

In the absence of this data-source - if a clear predictive relationship could be established between scheduled hourly (DAM) inputs and actual (EirGrid) values - then similar inputs could be constructed based on existing historical actual (EirGrid) datasets and the future expected projected demand and wind values (from the GCS). The analysis, however, indicates that there is insufficient evidence to establish a clear predictive relationship between these data-sources at this stage.

Differences between the scheduled hourly (DAM) inputs and the actual (Balancing Market) outcomes varied significantly by hour. There was no discernible trend underpinning these hourly differences within each month. However, there was evidence that the level of these input differences was reduced in summer months.

There is significant variation in the proportional representation of these system characteristics when comparing the DAM values with the gross actual values. This implies that in order to construct future expected scenarios which were based on DAM cleared values for the steady state without any changes to the generation fleet a significantly larger sample set would be required.

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[14] In this instance gross system inputs are represented by whole-of-system actual data as developed from SCADA readings or directly supplied by EirGrid.

However, this alone is insufficient since for forward-looking supply and demand it is unclear how much of it will clear through the day ahead process, or which types of future demand/supply participants are more likely to directly participate through the DAM.

Since part of the purpose of the backcast is to better understand how well the forward-looking model setup would replicate the historical behaviour, the backcast has been performed using gross actual historical values.

Backcast using scheduled (DAM) inputs vs actual (EirGrid) inputs

To confirm whether this approach is robust the model was tested over the backcast timeframe directly using historical DAM demand and wind values.

The aggregate outcomes on interconnector flows, generation, and prices were on average a very similar fit to those developed from using actual values. It was noted that in December and January the DAM wind and demand inputs captured the high-priced periods more accurately. However, in other months, the appropriateness of the fit was either similar or worse than those developed from the actual wind and demand inputs.

This test, however, indicated that using the gross actual inputs gave us a sufficiently sound representation of the DAM dynamics. The appropriateness of this fit should continue to be monitored as more actual live market data from the DAM becomes available.

7.2.2 Additional market elements

Minimum income conditions

The I-SEM introduced a complex bid format which allows participants to input offers with Minimum Income Conditions. These require that a certain income threshold is met for that generator across the day in order for them to be dispatched.

When the system is not in stressed conditions this offer-type typically has minimal impact on the market solution compared to a generator cost driven model which includes an uplift. This is because participants are always incentivised to shape all their trading behaviours based on making a profit against their estimate of the cost of supplying. For example:

- If a generator expects to already be running, has a high cost of start-up, and there is a risk of not being dispatched; then the participant will typically be incentivised to reflect a lower estimate of start/stop costs, and consequently a lower minimum income condition. This is similar to how an uplift algorithm applied to a similar plant will discover a good solution is to incur start-costs less frequently and to distribute the potential start-costs over a larger number of time periods, lowering the offered price and ensuring it is more likely to be dispatched in the market.

- If a generator expects not to be running, has a high cost of start-up, and there is the risk of being dispatched for a small number of periods at a marginally profitable price; then the participant will typically be incentivised to reflect a higher estimate of start/stop costs, and consequently a higher minimum income condition. This is similar to how an uplift algorithm applied to a similar plant will discover that higher start-costs would be incurred if the plant is switched on, and the higher cost would be distributed over a small number of potential running time periods. The resultant raised offered price will operate like a high minimum income condition by ensuring that the plant is less likely to be dispatched in the market when the expected income does not meet the profitability threshold.

The impact of these decisions is likely to influence generator dispatch in a similar way to how the uplift algorithms would. However, the overall market solution is unlikely to be significantly changed when there are a large number of substitutable generators at each stage of the supply curve. For a market which is not under stress[15] when any supplier shapes offers to exercise market power via the minimum income condition then the other suppliers would be incentivised to undercut their offer.

Under stressed market conditions the minimum income condition could also be used to reflect recovery of scarcity rentals. This would typically occur in the situation where there is significantly lower than typical intermittent generation in the market, and certain participants are confident they will be dispatched into the market.

If a participant is confident they will be dispatched into the market that day for a wide range of possible offer prices, then they are incentivised to increase the prices in their offers and bids and recover additional profit from the market. The minimum income condition is one of the mechanisms that can be used to ensure significant return on generation across the entire day. This allows participants to leverage the fact that the capacity they provide may be required to cover the peak time periods and recover a certain income across the day.

Instead of using the simple bids and offers to achieve the same outcome, the minimum income condition allows the market to achieve a least cost solution which, for example may result in higher prices across the day, rather than much higher peak prices.

In practice the intended impact of minimum income conditions set by a particular plant can be difficult to determine. For example, pricing shaped by true risk aversion could be viewed by another participant as an intentional method of procuring scarcity rentals. Based on analysis across the year it seems likely that during times of market stress participants did incorporate scarcity rentals or additional risk aversion in their bidding behaviours. The potential for these behaviours varied significantly by month, with the strongest potential seen in mid-summer months (June, July, August).

There is insufficient data at this stage to form a view on how these behaviours would be best represented in the model, and on whether they are likely to continue as the I-SEM matures. However, it is recommended that the relationship between low intermittent generation quantities, minimum income conditions, and bid behaviour more generally should continue to be monitored. If the next few years indicate a statistically predictable and regularly observable behaviour is shaping these market offers then it may well be

[15] A market could be considered under stress when there is low marginal capacity in the generation/supply balance. This is typically due to some combination of particularly high peak demand, particularly low wind, or large generation system outages.

appropriate to consider developing a custom uplift algorithm to better represent these scarcity elements in the I-SEM PLEXOS model.

In general scarcity rentals are not always a modelling problem – they can sometimes be an indication that refinements should be considered in the market itself. Typically, the appearance of scarcity rents is a sign of market stress which is an investment signal that more plant needs to be built. If there are persistent scarcity rents which are not naturally resulting in increased investment in plant with appropriate characteristics to meet the specific system conditions when they are incurred, then further regulatory analysis may promote better long-term SEM market outcomes.

Assetless traders

Assetless traders are a class of market participants which were introduced through the launch of I-SEM. These are participants trading in a way which is de-coupled from physical assets and can both buy and sell energy in the ex-ante markets.

In international electricity markets, assetless traders are well-established conduits for introducing additional liquidity and enabling a more dynamic transfer of different participants risk appetites and future expectations of market price and dispatch trends. However, their activities are always driven by two key elements – the willingness of a generator or demand-side participant to sell a volume of electricity to them at a given price, and the willingness of other participants or the market to purchase that electricity off them at a given price.

The price estimates which determine the willingness of participants to sell are driven primarily by their estimate of generation costs to produce the sold electricity, and secondly their belief that selling it at the received price is either more profitable or less risky for their company than trading it into the ex-ante markets themselves.

Likewise, the price estimates which determine the willingness of the ex-ante markets or other participants to purchase this electricity is based on their belief that it is either less expensive, or less risky than purchasing the same electricity directly from the market itself. Specifically, this means that they believe it is either less volatile or priced lower than the cost-driven market bids and offers they would reasonably expect to see.

In liquid traded electricity markets under an equilibrium state, the assetless traders will only have market-price setting power when they are acting as a proxy (directly or indirectly) for a unit which would itself have market-price setting power. This means that typically the aggregate unit dispatch and pricing outcomes remain largely similar. However, the uncertainty and time value of information may have been traded from one participant to another.

If there is insufficient market liquidity then assetless traders can, like generators, offer in such a way as to recover scarcity rents or to take advantage of market volatility. Again, there is no inherent reason why this should alter the fundamental economics of the market in a way which is differentiable from any other trading entity with a portfolio position in electricity supply or demand.

In general, the outcomes of this style of rational economic behaviour would be consistent with a generator-cost driven fundamental market model. Confirming whether assetless trader behaviour follows rational economic behaviour at steady state in practice would require at least a few years data.

Assetless traders are not explicitly represented in the model but assumed to be represented by generators and demand side participants willingness to purchase/sell electricity in accordance with their generation-cost driven estimates. At this stage there is insufficient evidence to infer either that assetless trader behaviour has or has not deviated from these norms under steady state. Similarly, a single year is insufficient to give a picture of how these behaviours may evolve over time.

7.3 Inputs

The key model inputs which were updated to reflect actual values across the backcast period are summarised in the table below.

Table 12 Backcast key historical inputs

Data Type	Data	Source	Comparison
Commodity pricing	Historical day ahead commodity prices and FX rates	Bloomberg	N/A
Commodity pricing	Fuel adders	RAs and data from generators	N/A
Demand	Actual hourly dispatch.	Developed from EirGrid 15-minute metered data	DAM offered demand quantities
Wind	Actual hourly dispatch.	Developed from EirGrid 15-minute metered data	DAM offered wind quantities
Interconnectors	Historical day ahead interconnector transfer capacities	ENTSO-E	DAM interconnector capacity levels
Outages/output restrictions	Historical outage and output restrictions (including forced outages)	System Operators	ENTSO-E Forward-looking weekly reports
Generator technical/commercial parameters	Includes VOM costs, operating costs and heat-rates. As per input validation.	Generators	N/A
GB prices	Actual hourly DA prices	N2 EX DA Auction Prices	ENTSO-E

Commodity pricing: Historical actual fuel prices, carbon prices and exchange rates are used to calculate the actual commodity prices in combination with actual fuel adders. The plant fuel prices are then fed into the model.

Demand and wind: Demand and wind actual historical profiles are created from actual hourly data and wind installed capacity data.

Interconnectors: Historical DA interconnector transfer capacities are applied to both Moyle and EWIC.

Outages: Historical outages provided by the TSOs across the backcast period are applied to the backcast model.

Generator technical and commercial parameters: The data provided by the generators has been used to update the backcast model. These include updates to heat-rates, ramp rates, min up and down times, VOM costs and start costs.

GB Price: Actual DA GB wholesale electricity prices are used to provide assurance in the backcast that the SEM model performs appropriately against real market price data. This allows us to consider the impact of the different potential GB models independently from other market model elements (see section 8.3.2).

The historical data for each of these categories are inputs to the backcast model. This ensures the real historical events which shaped the market outcomes are captured in the model inputs, so that model outputs can be expected to more closely match actual market results.

NOTE: The initial backcast period was carried out from I-SEM launch on the 1st of October 2018 until 30th June 2019, this was based on the data available when the backcast exercise commenced. Following months were then incorporated later in the process, prior to the event and seasonal analysis commencing. For these reasons, reported outcomes differ from those presented at the December 2019 Stakeholder workshop.

7.4 Outcomes

In this section the initial outcomes are outlined from backcast simulations with the input changes mentioned above. These represent the initial rough fit between model results and actual results based on the raw inputs alone before identifying any areas where the model was a poor fit for actual outcomes and re-calibrating the model to construct a better fit.

For the purposes of calibration GB electricity DA prices are forced to be equal to the actual historical DA prices. This demonstrate the model's ability to correctly simulate SEM price and dispatch outcomes assuming that the GB price is not impacted by the SEM. This was used as the basis for the initial outcomes, and the backcast calibration and refinement.

However, a key outcome from undertaking a backcast is to validate the appropriateness of the forward-looking model (including its representation of GB). Hence, the model outcomes produced using actual GB prices also comprises the first methodology as part of testing the GB model set-up for the forward-looking model as described in section 8.3.2.

The final backcast results in Table 16 through Table 18 below include values for the backcast using actual GB prices, as well as those using the selected GB model.

Historical data for model comparisons

In order to compare and later calibrate the backcast model outputs, the data summarised below was used.

Table 13 Historical data for backcast model comparisons

Data	Source
SEM DAM wholesale electricity prices	RAs
GB DA wholesale electricity prices	RAs
Expected interconnector transfer direction	RAs
Interconnector actual flows	RAs
Generation	RAs

Prices

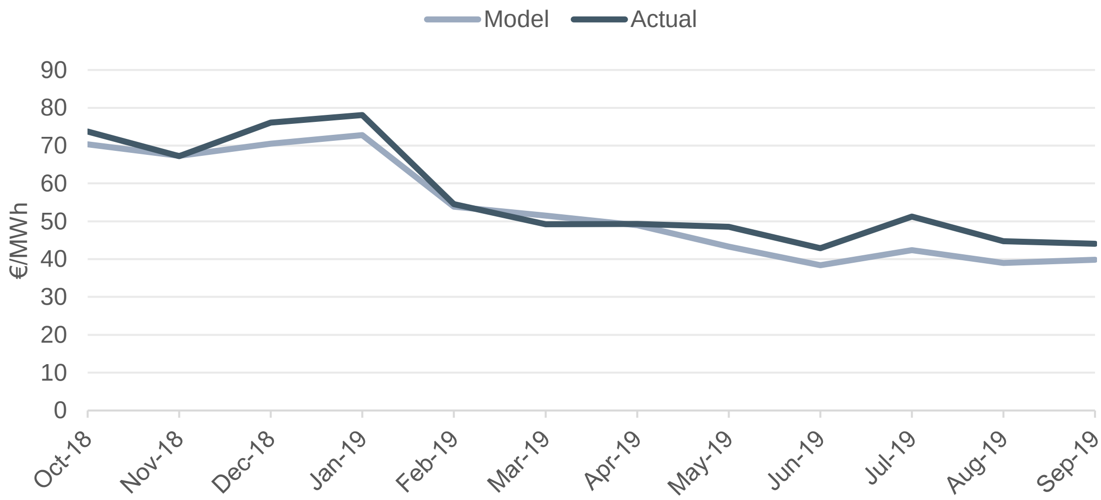
The following figure provides a comparison between modelled and actual monthly average DA prices. The modelled results are mostly in line across winter, apart from two winter months (Dec-Jan). However, the modelled results consistently underestimated prices across the summer months (May-Sep). Across the backcast modelling horizon (Oct 2019 – Oct 2020) the average modelled price is -5.8% lower than actual. This is a larger difference than the initial result reported at the stakeholder engagement in December 2019 (3.6% lower than actual) which was based on a backcast from October to June as data was not available beyond that point at that time.

Modelled prices across winter are within reasonable bounds, with most months falling within a ± 10% variation threshold, and the aggregate deviation is within a ±5% threshold. However, variation in modelled prices across the summer months exceeds these thresholds as will be discussed in further detail below. As this backcast is only observing a single year of data, and the deviation is only 0.8% more than the desired threshold, this may be a marginally acceptable result, but requires further exploration below.

Experience in other markets indicates that a ±5% threshold is an appropriate fit when fitting against 3-5 years of real market data. Given this backcast comparison is against a single annual sample and is fitted over the initial market time period it is reasonable to expect greater deviation between the modelled and market outcomes. To ensure a future-proof model it should not be over-fitted based on data from a new and evolving market. In light of this balancing act, and since the key price differences can be attributed to specific events where the market experienced stress, this result can be considered acceptable.

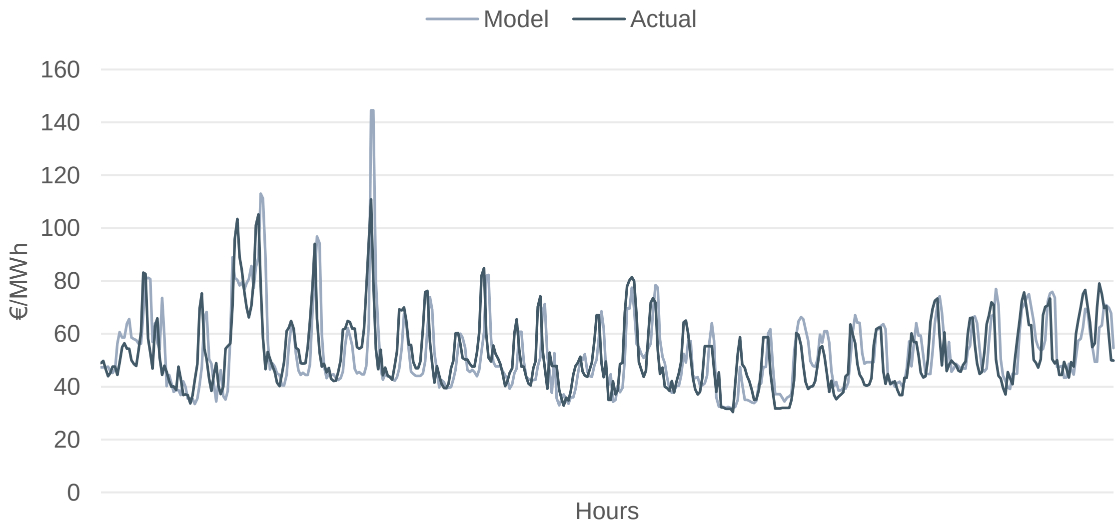
Event-based differences and differences in winter and summer months are explored in more detail in the sections below.

Figure 16 SEM DAM backcast price comparison



In general, at an hourly granularity, prices are a strong representation of real market outcomes. While there are some variations in the price curve compared to actual outcomes the shape of the curve mostly captures the peaks and troughs on aggregate. The key limitations discovered were that some peaks and troughs do not have the same depth as those observed in the market, that prices were consistently slightly lower across summer and that during specific times of atypical low wind generation the modelled results didn't fully capture the market price volatility. An indicative period is shown on the graph below, as can be seen, the greatest variation tends to be in the peak priced periods. However, there are some of the areas of worse fit which will be described in greater detail in section 8.1 and section 8.2 below.

Figure 17 Hourly price comparison – indicative period 23/03 – 09/04/2019



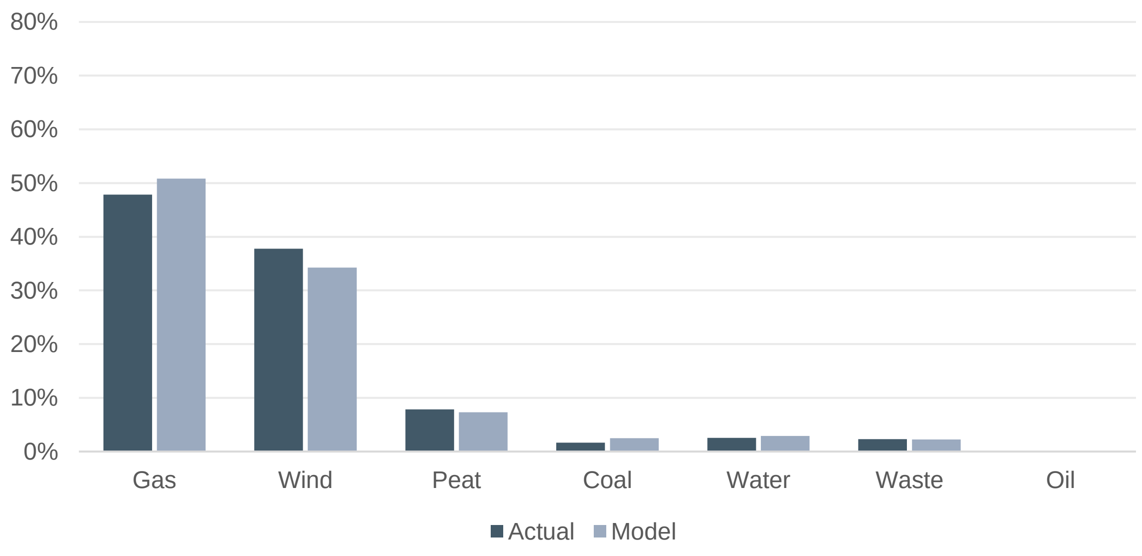
Generation

The following figure describes the comparison between actual and modelled generation. These comparisons were carried out throughout the backcast period. This analysis is extended to observe generation across baseload, mid-merit and peaking plant types, and in some representative instances investigated to a unit level.

In general, the generation split per fuel category is a strong match with all categories within a 3% range for annual average. The largest differences were driven by higher gas dispatch levels than was historically seen. The cause of this was discovered to be high interconnector flows. The interconnector flows themselves will be discussed in the section below.

Wind has been excluded from the graph as it is an input which forces the model to generate actual historical generation.

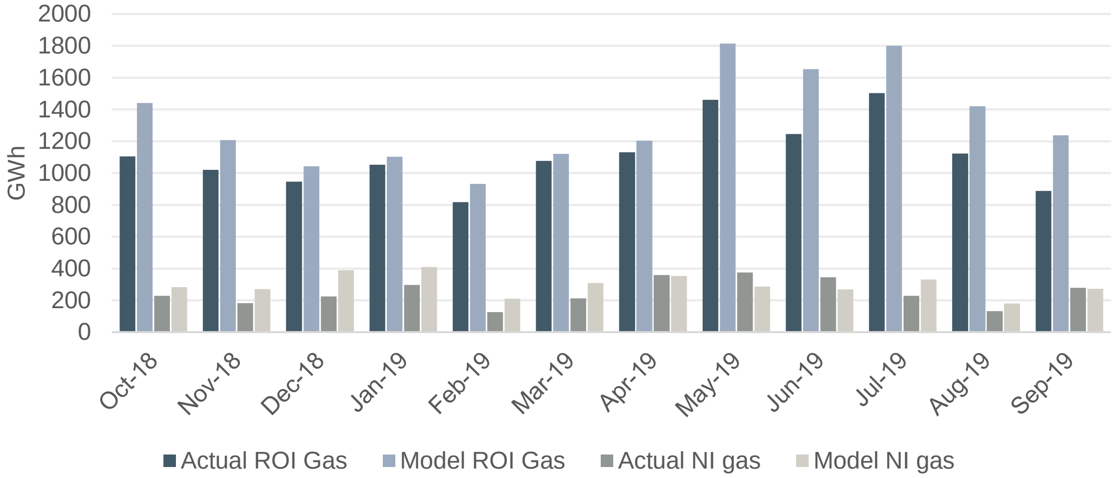
Figure 18 Generation split comparison per fuel type – backcast vs actual



Note: Generation split refers to percentage of total generation met per fuel category

The largest differences were seen in gas generation dispatch – the differences were largest for the Republic of Ireland gas generators across the summer months. This appears to be a response to lower modelled prices for the SEM. These lower SEM prices in the model resulted in transfer from the SEM into GB being more economically efficient in the model. However, high SEM prices in the market meant transfer from GB into the SEM was more economically efficient in the market outcomes. For the NI gas generators, the greatest differences were seen in December and January. These differences may be a contributing factor in why the market-based scarcity events (described in section 8.1) were not replicated fully by the market model.

Figure 19 Monthly gas generation comparison modelled vs actual



Interconnector flows

As part of the initial backcast review, the differences between actual and modelled interconnector flows were explored. Reviewing the initial flow results against actual flow in Figure 20 the model appears to be overestimating flows from west to east and underestimating flows from east to west throughout the year.

The key drivers of these differences seem to be:

- **Lack of differentiation in the modelling of GB supply curve** - while the GB price is set to replicate actual values, this price is available uniformly across the entire transfer capacity without transmission limits or competing alternatives. This means that when the GB price is higher than the SEM price the model is incentivised to transfer energy to GB up to the full available capacity of the interconnectors. In practice the interconnector flows tend to be more nuanced reflecting the GB's multiple different supply options. This is particularly the case in trading periods where there is high price volatility in GB.

- **Unit commitments and uplift in Ireland** – the high flows created by the inelasticity of GB price modelling means that modelled generators in the SEM will stop and start less frequently. The continued value of transfer into GB will incentivise them to remain on, rather than switching on and off as they would in practice. This lowers the total quantity of start-costs which are being recovered via the uplift mechanisms. The longer run times and generation volumes also mean that these costs are spread over a much larger volume, reducing their impact on each individual marginal price, and resulting in a SEM price which is lower than actual. In general, the reduced uplift in Ireland means that on average the GB price is higher than the price in the SEM incentivising flows to increase further.

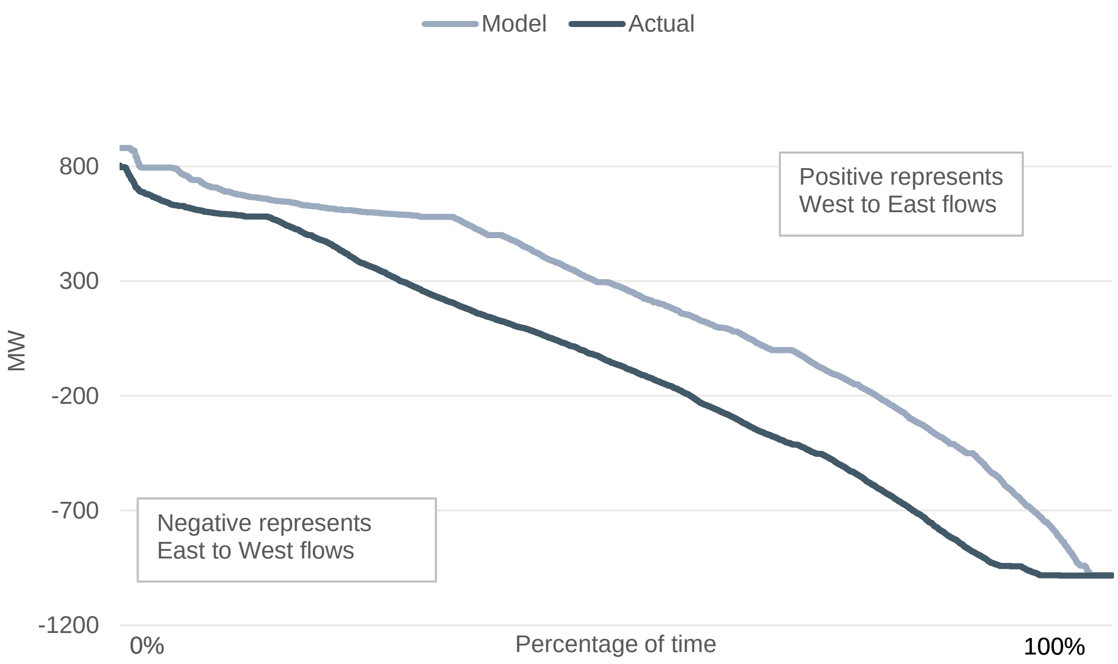
- **Additional seasonal uplift in Ireland across summer** – the model outcomes imply that there is an additional uplift to offered generation across summer which is not currently captured by the model parameters. This could be due to unusual conditions in the one-year sample used to calibrate the backcast against, and there is a risk that introducing such an element may over-fit the model. However, if future backcasts consistently show this effect then the option of manually replicating this uplift should be considered.

There appear to be some seasonal differences in relation to flows. The model produces a less compelling fit to historical behaviour in summer months. This is explored in more detail in the sections below.

Interconnector flows were the key driver of differences between aggregate generation quantities described above. Interconnector flows also appeared to have a dampening effect on peak prices during times where the system would otherwise be undergoing periods of stress due to lower intermittent generation levels.

Flows and different GB modelling approaches were explored and are covered in more detail in section 8.3.2.

Figure 20 Interconnector flow duration curve – backcast vs actual



Note: Data refers to hourly flows for the backcast period: 1st Oct 2018 to 30th June 2019

8 Backcast calibration and refinement

Once the initial backcast is performed then the initial results are used to identify areas where the market model did not replicate historical behaviours well across the backcast time period. These areas are then explored to discover what is driving those differences and evaluate whether or not the learnings from these are appropriate to be integrated back into the model.

8.1 Event-based analysis

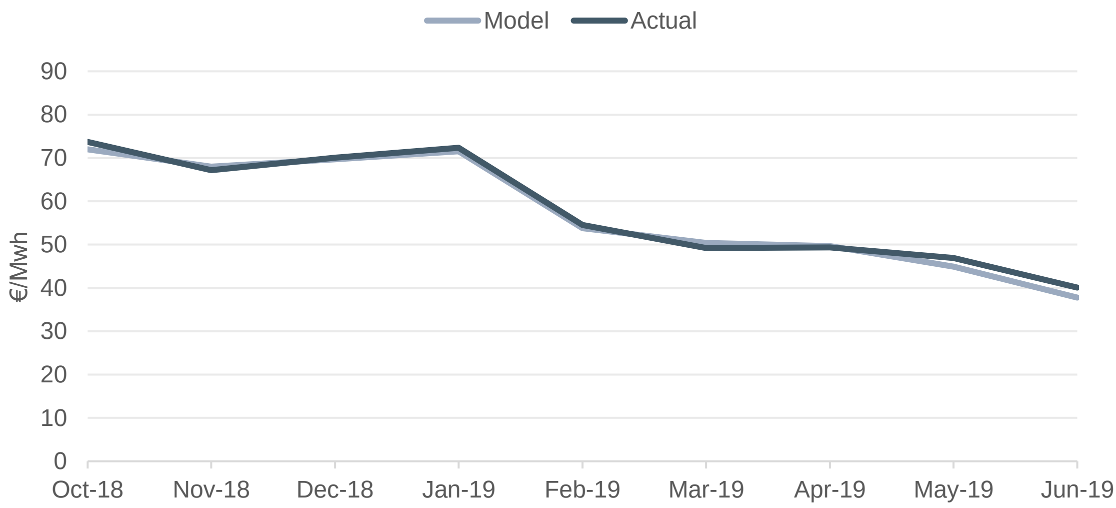
Winter events

When comparing actual market results against modelled results it was evident that the winter months of December 2018 and January 2019 were less of a match compared to other months

Following further investigation, it appeared that this was primarily due to limited and isolated peak hours where the model was not picking up the scale of peak prices observed in the SEM market.

Further investigation revealed that these limited hours where the model was not reflecting higher market prices were usually identifiable as having atypical low or volatile wind generation. Figure 21 illustrates the monthly SEM average DAM price comparison if these limited hours are omitted. The comparison shows that when excluding these atypical hours (~50 hours in each of the affected months in winter) the overall model-fit through winter was very strong.

Figure 21 DAM SEM price comparison (excluding winter atypical intermittent generation hours)



Summer events

The summer months of May 2019 through September 2019 less closely matched market outcomes compared to other months.

A similar investigation into the May through September time period identified further periods where atypical low or volatile wind was resulting in higher market price outcomes from the market than those shown in the model. There were a larger quantity of these times across the summer months – partially due to the specific annual weather pattern, and partially because at lower load levels there are typically more units which are in an offline state. However, in absolute terms these market prices did not appear to be triggered solely by system scarcity. Further units in the market were available to be dispatched but were not dispatched in the market solution.

These outcomes were distinctly different from those seen in December and January – in the winter events the PLEXOS model replicated a high peak price, but the height was not as large as that seen in the market. In the summer events there was very little additional volatility shown in the PLEXOS model solution, while the market had moderate and sustained higher prices.

Six key examples were identified, each spanning one to six days, and with at least one occurring in each of the summer months. Given the frequency with which these events were occurring within this season for a given year this seems to indicate that the PLEXOS model may not perform as well under these periods of very low wind. However, since there is only a single year of data it is difficult to determine whether this was due to unusual annual conditions, or due to a systemic modelling methodology element.

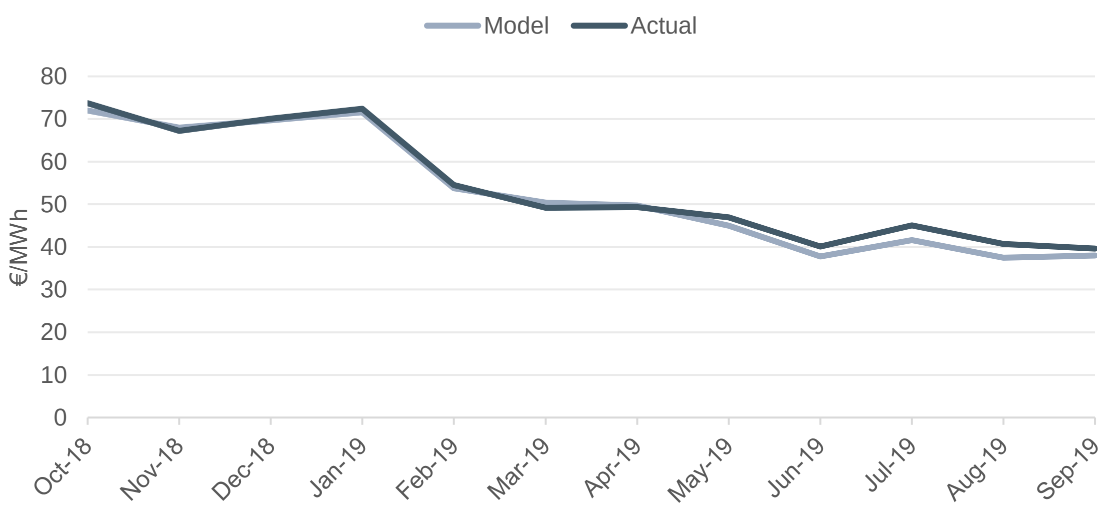
In market terms a possible cause for this difference is that these underlying conditions result in heightened market risk for participants. A given unit may not be confident whether market prices and dispatch outcomes for their unit are likely to justify the start-costs, and so may either bid higher prices to manage their risk, or use higher minimum income conditions to ensure they are only dispatched when they are confident of making a profitable return on generation.

These price events may also be difficult to replicate in the PLEXOS model where there is significant within-day wind uncertainty. The PLEXOS model uses perfect foresight of the daily wind forecast when scheduling units. This exposes units to lower risk when incurring unit commitment costs, as the actual wind generation values are already predicted accurately.

If these summer events continue to be seen when a backcast is performed over multiple years of data, then it is unlikely to be due to unique annual conditions. If so, then options should be explored for better modelling summer-time price volatility in the PLEXOS model.

In order to identify overarching seasonal price trends in the following section, these higher price volatility outcomes are normalised. This produced an annual set of prices as shown on the graph below. As will be discussed in section 8.2, even once these more volatile trading periods are excluded from the summer months there continues to be lower prices produced by the model during the summer season. Once these extreme price events were removed the backcast price variation improved from -5.8% variation to -2.1% price variation from observed actuals. These events accounted for ~50-100 hours in each of the affected summer months.

Figure 22 DAM SEM price comparison (excluding all atypical intermittent generation hours)



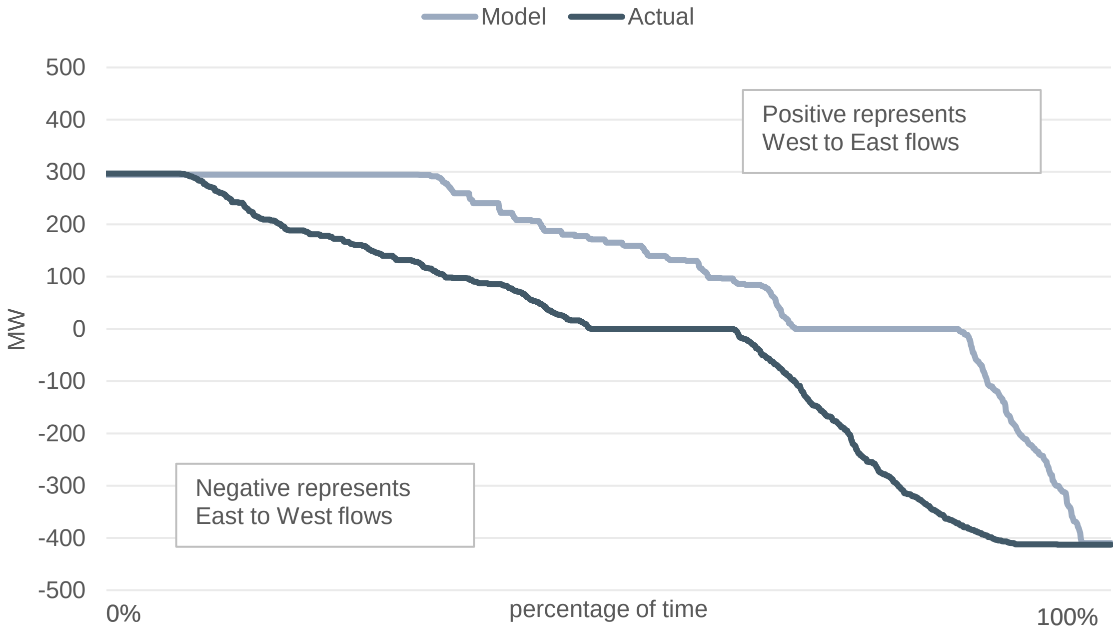
8.2 Seasonal analysis

In the backcast outcomes two notable seasonal trends were evident – both of which were directly linked to interconnector flows.

The first of these was that the summer months showed stronger evidence of slightly lower average prices with a depression in prices spread right across the time period. This trend was different to the event-driven differences described above where the difference appeared to be driven almost exclusively by the small number of price-spike periods which were not reflected fully in the model. The scale of this difference can be seen once extreme pricing events are omitted as shown on the graph in Figure 22 above.

The second of these was that interconnector flows from the SEM to GB were significantly higher than the historical outcomes across those summer months, as shown in Figure 23 below.

Figure 23 Flow duration curve comparison May-June 2019



Model outcomes under different model iterations, revealed that the higher interconnector flows from SEM to GB were partially due to depressed average prices in those months. The lower prices in the SEM meant that GB was consistently the higher priced market of the two markets. This meant that the model outcomes favoured interconnectors flowing from SEM into GB. In comparison, in the historical outcomes, SEM would have regular periods of prolonged higher prices than GB. In these time periods the interconnector would flow strongly from GB into SEM.

Likewise, it was discovered that the high flows in the model from the SEM into GB were both lowering prices in the SEM in some time periods and increased by the lower SEM prices.

This may partially be due to the fact that some of the units which were mid-merit or peakers in historical outcomes were running as if they were baseload. Since these units started and stopped less frequently, they had fewer start costs which required recovering through the uplift mechanism and these costs were distributed across higher generation values. The uplift values across these months were lower in consequence, which was enough to ensure they were lower than GB.

Additionally, however, there is evidence that the portions of the available capacity which is in the market is being offered above the cost and uplift level replicated by the model. This may be due to risk-aversion and learning behaviours, unusual weather, or scarcity rentals being accrued for certain segments of the supply curve.

Since the backcast calibrates to a single year of data it is possible that this mark-up is due to specific annual characteristics. However, if this continues to be observed in future backcasts then it is recommended that further analysis be undertaken on how different classes of plant are being dispatched into the market, and what this implies for their offer pricing characteristics.

One of the key drivers of the scale of transfer to GB was again the lack of variability in GB prices under different supply conditions. This is worsened across the summer months as typically there is lower demand, and so the GB market price formation is more sensitive to shifts in intermittent generation supply. Likewise, when there is a smaller number of mid-merit generators likely to be committed to the market then those generators are likely to have additional uplift incorporated into their offered prices to reflect their unwillingness to be switched on unless they are guaranteed a profitable return.

The calibration analysis process indicated that the best way to replicate market conditions was to re-evaluate different methods of representing GB available prices and quantities in the model. This is described in further detail in section 8.3.2 below.

8.3 Model

8.3.1 Mark-ups and uplifts

Both the SEM and Korean uplift methodologies were assessed against the SEM DAM results. It was discovered that while both methodologies were a good fit for the wintertime-period, the Korean uplift methodology was a slightly stronger fit across the total time period.

Despite being a stronger fit overall for the backcast time period, the Korean uplift methodology did not produce mark-ups which were as high as those seen in the market across the summer months. This effect was seen consistently across the majority of time periods.

As described in section 8.2 above this difference was partly attributable to the high interconnector flows, and corresponding low volatility in unit commitment for mid-merit plant.

However, there was some indication that there may be an additional mark-up component contributing to the price formation. It is possible that this was due to additional uncertainty in the market from the unusually hot weather during some parts of these months. Equally it may also be due to learning behaviours and risk aversion as participants attempt to ensure they make profitable decisions as they encounter their first summer in the new SEM market.

It is recommended that the summer months continue to be monitored to determine whether this additional uplift trend continues to be present and is statistically significant. If it does persist then this may lead to a further review of the market uplift methodology.

In performing the model runs the existing confidential mark-ups have been retained. These fall into three categories:

1) Those that represent an unwillingness to bid the final portion of a unit's capacity into the market based on costs alone

2) Those that represent an unwillingness to keep plant running overnight

3) Those that incorporate price differentiation to mid sections of a heat-rate curve for a unit.

It is unlikely that any of these elements would have been eliminated by the launch of I-SEM, and so the most prudent way forward is to retain these. However, these are confidential in nature and are not universally applied. Therefore, it is recommended that once multiple years of data (post I-SEM) is available, that some basic analysis be undertaken on differences between market dispatch outcomes and model dispatch outcomes for various categories of plant. This could provide a basis for some simplified replacements to these mark-ups alongside a publishable and transparent methodology for other market participants to construct equivalent elements for their own modelling.

8.3.2 GB modelling and interconnectors

The interconnection with the GB market provides opportunities for participants in the SEM. It can help meet demand requirements at a lower cost, provide security of supply and ensure intermittent low carbon energy is best utilised. Therefore, there is a need to represent the interconnection with GB via the Moyle and EWIC interconnectors appropriately in the SEM PLEXOS model. This was analysed as part of both the backcast and forward-looking model validation.

Ideally, the full GB market would be modelled to the same level of detail as the SEM, however this would be very computationally intensive to run, and would be difficult and time-consuming to maintain. For these reasons GB has historically been represented through a simplified approach which approximates the residual GB supply/demand curve which can impact on the SEM via the Moyle and EWIC interconnectors.

The key components which are important for modelling a representative supply curve for GB are:

- **GB Price Representation -** Developing a set of representative prices which represent the willingness of suppliers to supply energy at a given time.

- **GB Capacity Representation -** Developing a set of quantities associated with these prices representing the supply/residual demand curve elasticity. These identify how much energy can be released or served at a given price level before the market will move to a higher price category.

- **Technical Constraint Representation** - Developing a set of fixed system limitations, either technical or economic constraints which represent the costs or physical requirements associated with certain behaviours (e.g. start/stop, or minimum loading).

- **Representing Variable Influences -** Developing a representation of risk and variable elements that impact on the available supply/residual demand curve (e.g. intermittent wind or shaped demand).

Additionally, modelling methods must be both:

- **Maintainable** – this means that the methodology can easily be refreshed and revised. Thus, changes in the underlying market conditions can be quickly and consistently integrated into the model.

- **Forward-looking** – this means that the methodology can be used not only for the backcast but also for the forward-looking validated model. Using actual GB outcomes can be good for historical analysis but is not necessarily robust into the future as the future GB outcomes will be dependent on exogenous factors such as gas prices and carbon prices.

Six different methods were tested against the backcast results and evaluated based on the criteria described above. It is noted that there is a significant seasonal difference in fit. In general option six was discovered to be the most appropriate due to its balance of strong system representation and maintainability. These options are described in greater detail below.

Table 14 Tested GB modelling methods

No.	GB modelling method	Price	Capacity	Technical	Variable influences	Maintainable	Forward looking
1	Matching GB prices exactly	🟢	🟠	🔴	🔴	🟠	🔴
2	Heat-rate regression against GB prices	🟠	🟠	🔴	🔴	🟢	🟢
3	Heat-rate regression against GB gas prices with vertical segmentation	🟠	🟠	🟠	🔴	🟢	🟢
4	Heat-rate regression against GB gas prices with fixed component	🟢	🟠	🔴	🔴	🟢	🟢
5	Heat-rate regression against GB gas prices with horizontal segmentation	🟢	🟢	🔴	🟠	🟠	🟢
6	Heat-rate regression (with fixed component) against GB gas prices with horizontal segmentation and intermittent generation	🟢	🟢	🟠	🟢	🟠	🟢

For the purposes of the explanation below the following terms are used as follows:

- ❑ Vertical segmentation is used to describe splitting capacity over several identical units (for example an 800 MW unit with a mid-merit heat-rate may be split into 4x200MW units with a mid-merit heat-rate)

- ❑ Horizontal segmentation is used to describe splitting capacity into several units with different heat-rate characteristics (for example a 800 MW unit with a mid-merit heat-rate may be split into 1x400MW unit with a baseload heat-rate, 1x 300 MW unit with a mid-merit heat-rate, and 1x 100MW unit with a peaker heat-rate).

The key options were as follows:

1. **Matching GB prices exactly** – The representation which was used for the initial backcast calibration and analysis was one in which GB prices are forced to exactly equal the historical prices seen in the GB market. The GB demand and generation capacity is set so that there is sufficient capacity for full transfer across both EWIC and Moyle either into GB from the SEM, or into the SEM from GB.

2. **Heat-rate regression against GB gas prices** – This is the representation which was used in the previous validated model. To form this representation annual historical GB prices were segmented into winter and summer; and further segmented according to trading period for both key seasons. A regression analysis was performed between these prices and the associated daily GB DA gas prices to determine a representative set of heat-rates. In each of these two seasons the full generation capability of GB was represented by a heat-rate. These prices were further raised by incorporating GB emissions costs into the fuel cost, and by introducing wheeling charges to the interconnectors.

3. **Heat-rate regression against GB gas prices with vertical segmentation** – This method builds on method 2 described above. However instead of representing GB as a single unit the supply in GB is split into 4 different units. Each has the same heat-rate characteristics, but different maximum capacity, minimum stable levels and minimum up-time introducing a unit commitment component to the GB model.

4. **Heat-rate regression against GB gas prices with fixed component -** This method is similar to the regression methodologies described above, however instead of being a fully variable heat-rate, the regression was performed assuming there was a non-zero constant element. This non-zero element in the GB price analysis was typically a fairly good fit to the lower priced baseload elements in the system which would not directly have emissions included in their calculation (e.g., wind and nuclear).

5. **Heat-rate regression against GB gas prices with horizontal segmentation –** This methodology built on the regressed GB heat-rates (in this case the heat-rates with an added constant component, as they were a better fit for market outcomes). However, portions of the supply curve were identified to be separated out and priced as baseload generation, or as peakers. Baseload generation pricing was based on the constant element identified in the heat-rate regression. Meanwhile the peaker representation was priced seasonally in accordance with the peak prices observed in the market.

6. **Heat-rate regression (with fixed component) against GB gas prices with horizontal segmentation and intermittent Generation –** Adding intermittent generation introduced a wind generation component to the supply curve in GB. This was tested over options 2-5, but the strongest outcomes were seen with option 5. Across all of the options it particularly improved the representation of interconnector flows across the summer months. As this is the chosen model it will be described in further detail below.

Option 6: Heat-rate regression (with fixed component) against GB gas prices with horizontal segmentation and intermittent generation

This is the recommended methodology as it produced the strongest fit to actual market results, as well as representing a good estimate of systems behaviours.

Analysis of different explanatory variables identified that the most significant contributor to GB price formation was the GB gas price. Using a series of regressions (across each hour, across price data split into summer and winter seasons) a variable heat-rate component and a constant component were identified. These contributed to price formation, alongside emissions costs.

Using price and flow cluster analysis it was identified that while the resulting equations were a good representation of GB prices on average, they did not capture some of the variation which was seen in practice in the system. Particularly that, at times, higher or lower priced generation was likely to dominate price and flow outcomes.

This indicated that a better result would be observed where the available capacity in GB was represented by several generating units, each with a different price. For simplicity the approach used included:

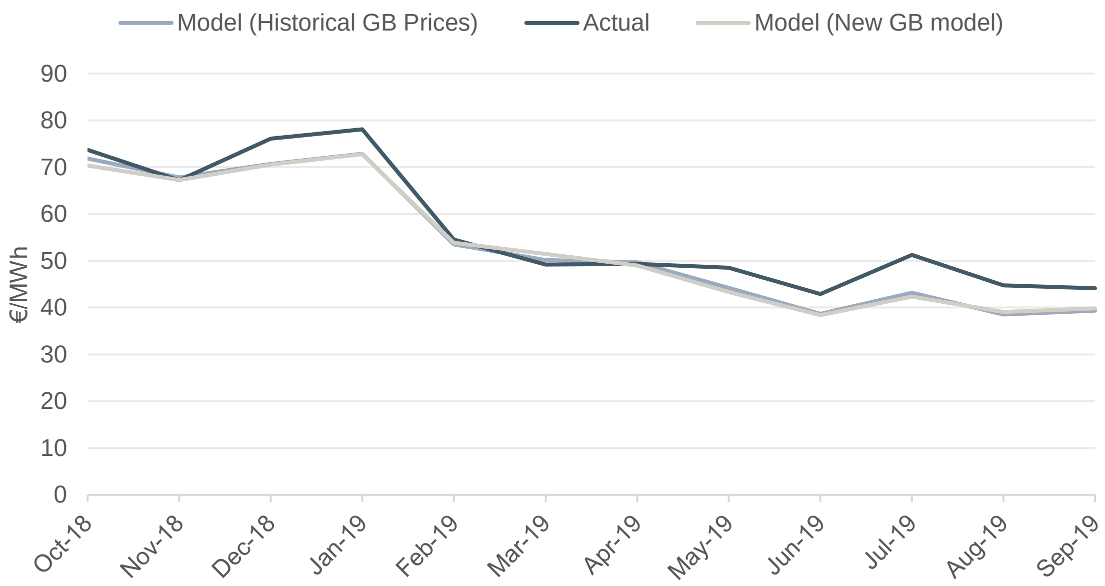
- ❑ a single unit at a baseload price (with a bid price equal to the fixed component of the regression outcome);
- ❑ a single unit which acted as a mid-merit plant with heat-rates according to the regression outcomes;
- ❑ a single peaking unit (with a price based on observed seasonal peak market prices); and
- ❑ a single intermittent wind generator (with capacity factors based on ROI, as the highest impact on SEM solutions occurred when capacity factors were correlated between the two islands).

The capacity of each of these generating plants was determined per season based on cluster analysis of flows. However, when this analysis was performed across the winter months it produced outcomes where the baseload unit, intermittent generation and peaking unit each had a zero, or very small capacity associated with them. For this reason, the GB model for winter is substantively the same as that which would be produced by Option 4.

This methodology produced strong results particularly across the summer months. Outcomes were driven by the good representation of GB prices, available quantities, and a good representation of the residual supply curve. However there continues to be no direct representation in the methodology of the unit-commitment trade-offs between units in GB and those in the SEM.

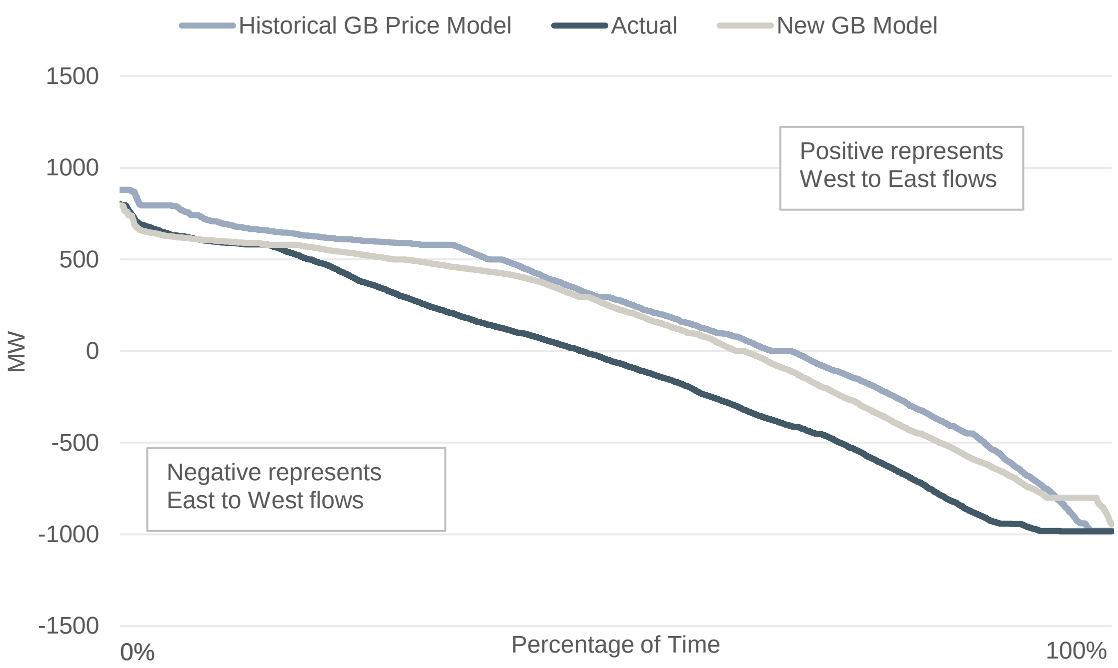
The GB model produces a substantively similar shape of SEM pricing outcomes as using historical actual GB prices. However, there is a small reduction in price quality from -5.8% lower than actual to -6.1% lower than actual.

Figure 24 Monthly average prices (comparing new GB model to actual historical and GB model with historical GB prices)



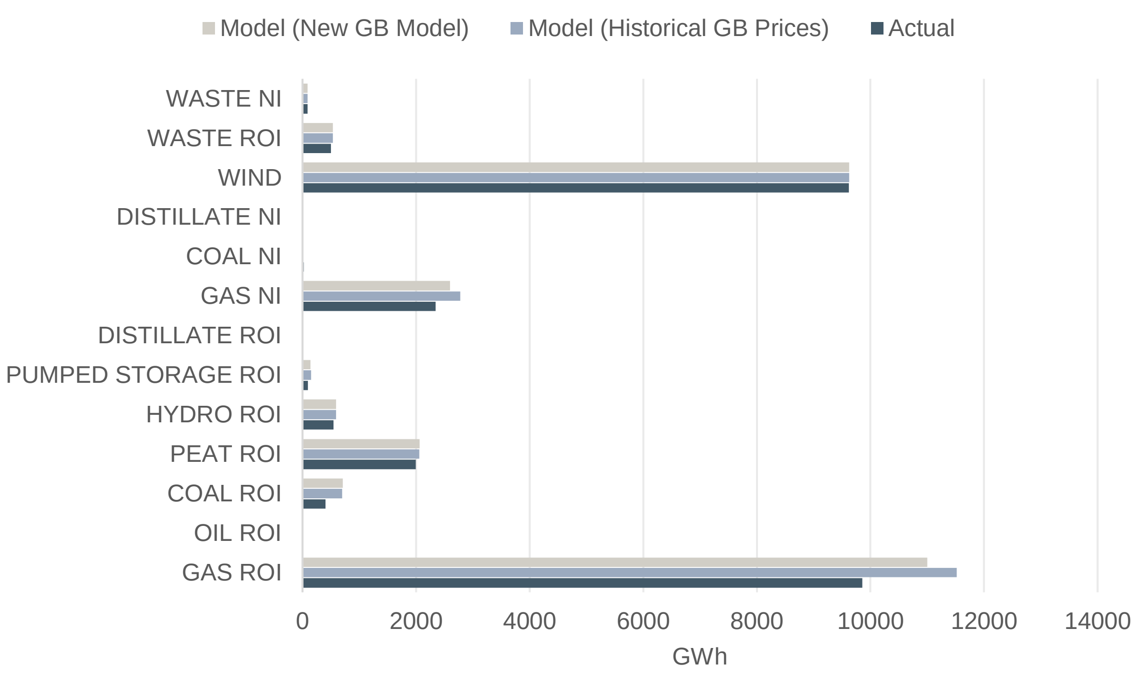
Interconnector flow representation of the revised GB model is superior to results using historical actual GB prices.

Figure 25 Interconnector flow duration curve (comparing new GB model to actual historical and GB model with historical GB prices)



The closeness of fit between the model and generator dispatch outcomes is also enhanced by the new GB model.

Figure 26 Annual total generator dispatch outcomes by plant type (comparing new GB model to actual historical and model with historical GB prices)



Wheeling charges

Wheeling charges are a model element which was introduced to the SEM PLEXOS model in order to replicate the market interconnector flow outcomes more accurately. These are costs applied to the flow across the interconnector and are used to adjust the price differences required between the two markets before flow becomes economic in a given direction.

The wheeling charges which were included in the previous models were included so as to calibrate interconnector flow outcomes to more closely resembled market outcomes. These were not designed to replicate the fundamental economic drivers underpinning interconnector flows. They also require re-calibration to be used appropriately under MIP as opposed to RR.

The inclusion of wheeling charges over the backcast time period worsens pricing outcomes across the year. It does, however, improve interconnector flow outcomes across the summer months.

It is recommended that these wheeling charges be removed. This is partially due to the new GB modelling methodology which improves the modelled interconnector flows. Also removing these constructed elements ensures that the model development will continue to evolve based on market fundamentals. Regular inclusion of constructed elements could cause over-fit to historical behaviours rather than a model which can consistently predict future expected market outcomes.

8.4 MIP vs RR

Using a MIP-based approach across the backcast period produced mixed results. There was an improvement in summer price and interconnector outcomes, while the representation of winter market outcomes worsened. The benefits and drawbacks of each approach are discussed in section 6.5 above.

In order to isolate the impact of different proposed methodologies from other system-calibration elements analysis was undertaken across the backcast time period in three stages.

1. **Identifying the impact of MIP on SEM alone:** For this analysis the energy generation and prices were fixed to exactly match historical levels so that there was no potential for additional transfer to/from GB above historical levels.

2. **Identifying the impact of MIP on SEM including interconnector flows**: For this analysis GB offer prices only were forced to exactly match historical prices, while flows themselves were permitted to vary.

3. **Identifying the impact of MIP on specific unit behaviours**: This was analysed at a high-level across the backcast time period, and in greater detail for two key problematic time periods where both the MIP and RR solvers struggled to replicate real market outcomes.

The outcomes from testing MIP on SEM alone (with fixed interconnector flows and GB prices) showed a positive impact on aggregate annual prices, while leaving aggregate dispatch and interconnector outcomes largely similar. This is largely due to MIP resulting in a smaller price gap between modelled and actual prices across the months of July and August. MIP increased the volatility of modelled prices in winter peaks in a manner that was not observed in the actual market outcomes.

However, when testing MIP on the SEM including interconnector flows (with only GB prices fixed) there was no significant positive impact on aggregate annual prices. Nonetheless, interconnector flows and generation dispatch outcomes were improved in the summer months.

Finally testing MIP on the SEM model using the GB modelling methodology outlined in section 8.3.2 above there were observable improvements in the aggregate model solution for summer months, and a worsening across the winter months. This was observed across pricing, interconnector flow and aggregate generation dispatch outcomes.

Nonetheless the key cause of price differences in the backcast across the summer months was due to events correlated with low wind generation or high wind generation volatility. Both MIP and RR were equally unable to replicate this market behaviour.

When identifying the impact of MIP on specific unit behaviours it was noted that:

- for baseload plant the two methodologies performed equivalently well in replicating market outcomes.
- for mid-merit plant RR was a better replication of some plant dispatch, while MIP provided a better replication of other plant dispatch.
- for peaker plant, RR generally provided a more realistic profile for regularly activated peakers.

In addition, event analysis was undertaken observing some periods for which the backcast was unable to develop a strong fit, as well as some which the backcast was able to replicate well. It was discovered that for the time periods where the fit was initially poor that there was no significant improvement to the dispatch outcome for the representative units from moving from the RR to the MIP method. However, for summer hours where the fit was initially fairly good there was a small improvement. Whereas for winter hours where the fit was initially fairly good the MIP method worsened some outcomes.

These mixed results signal that while MIP shows some potential for replicating some market conditions, it also has disadvantages. Likewise, a change in modelling methodology may not be sufficient to replicate some of the dispatch and unit commitment outcomes which occur when the market is under stress (in these cases due to low wind).

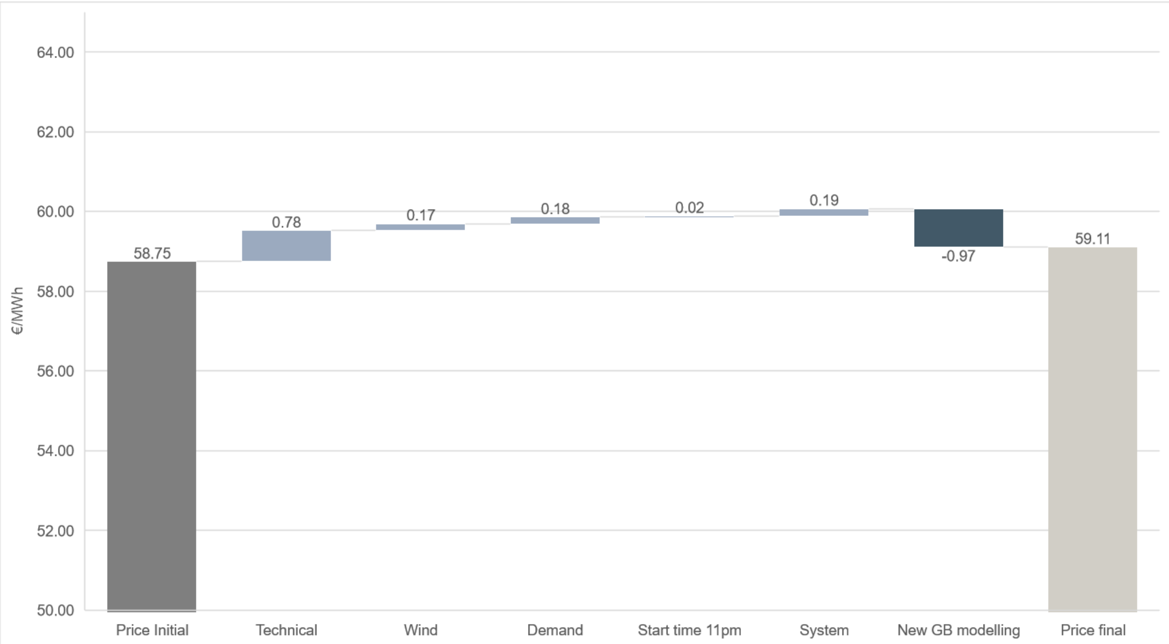
NOTE: Since wheeling charges have been removed from the model, the model no longer requires significant recalibration to be appropriate for running using the MIP methodology.

9 Conclusions

9.1 Summary of key model updates

The following figure provides a summary of the key model updates and the impact they had on the SEM annual average price in 2020. It is an indicative model simulation of 2020 keeping the commodity and exchange rate assumptions constant as per Table 8. It is important to note that the impact of these changes will vary year on year.

Figure 27 Indicative impact on 2020 SEM average annual price from key model updates



With reference to the figure above the individual elements are briefly summarised below. For further detail on these updates please refer to sections 3 to 8.

Technical: includes the update of plant technical parameters, retirement and start dates, VOM costs and operating costs.

Wind: the update of annual wind capacity projections as per GCS 2019 as well as the update of the base wind profiles used to 2014-2018.

Demand: the update of annual demand projections as per GCS 2019 as well as the update of the base demand profiles used to 2014-2018.

Start-time 11pm: update of model start-time from 6am to 11pm to reflect actual market start-time.

System: includes updates to outages, TLAFs, DSUs, batteries, embedded generation.

New GB modelling: updated GB modelling approach.

The net effect of all model updates compared to the previously calibrated model is an increase of +0.36 €/MWh on the annual average price in this indicative example of a 2020 simulation.

9.2 Summary of backcast findings

A backcast with only one year of market data is inherently limited, and the backcast findings were acceptable once the impact of these limitations were taken into account. The backcast outcomes were fairly strong across the winter period, but weak across the summer period. This was true across pricing, interconnector and generation dispatch outcomes.

Given there is only a single year of data available across this time period it would be risky to recommend substantive changes to the model in response to the differences observed in the summer months at this stage. These outcomes may be due to specific annual conditions (the key price differences were correlated with particularly low wind). Furthermore, there are also likely to be learning behaviours exhibited in the market as participants transition from the structured bid requirements of the SEM, to the less restrictive bidding strategies in the I-SEM.

To address these differences performing a further backcast once another 1-2 years of market data is available is recommended.

Annual-specific conditions are difficult to replicate consistently in a forward-looking model, since the wind outcomes in the future will be uncertain for all trading periods, and so the market signals which incentivise these outcomes would be difficult to replicate.

Regular and recurring differences between market uplift/mark-ups and modelled prices however could be partially addressed either through introducing customised uplift, customised mark-ups, or converting from the RR model to a MIP model.

The high-level backcast outcomes are as detailed on Table 15 below.

Table 15 High-level backcast outcomes

	Historical	RR-PLEXOS (New GB model)	RR-PLEXOS (Historical GB prices)	MIP-PLEXOS (New GB model)
Annual average price	€56.60	€53.20	€53.40	€54.40
Annual interconnector flows (Into GB)	1600 GWh	2353 GWh	2786 GWh	1963 GWh
Annual interconnector flows (From GB)	2572 GWh	1503 GWh	1283 GWh	1987 GWh

The RR model price outcomes are just outside of the range expected to be seen on a 3-5 year backcast. Following analysis of key causes, these are within the expected tolerance for a backcast across a single year. However, further backcasts need to be undertaken to ensure these differences are due to annual characteristics rather than a persistent trend. As expected, lower price outcomes in the SEM result in interconnector outcomes with higher transfer from Ireland into GB than in market results. Interestingly these results are consistent both using the GB modelling methodology and where GB prices are set at historical actual prices. This implies that the key issues which prevent a strong replication are market behaviours within the SEM.

The key differences are driven by highly priced time periods where there was low or volatile wind generation in the market. If these time periods are omitted from the market data, the annual average historical market price would be €54.06 – which is within an acceptable +/-5% bound for all of the backcast outcomes specified on the table above. This reinforces the recommendation to explore the market drivers behind these events in greater detail.

The MIP backcast outcomes aggregate annual price outcomes were higher – these were within a ±5% variation from the historical pricing outcomes. This reflects stronger market outcome replication in the summer, but worse market outcome replication in the winter. Also, at a monthly level MIP (like RR) continues to struggle to replicate the low wind, high price events across the summer.

9.3 Recommended changes and further actions

The key changes that are recommended to the market model based on this model validation and backcast exercise are as follows:

- ❑ Move to a market start-time of 11pm
- ❑ Update the PLEXOS version to 8.1
- ❑ Introduce GB modelling based on a gas price-based regression combined with horizontal segmentation and the addition of intermittent generation (particularly for summer)
- ❑ Remove wheeling charges

The key elements which were explored and it is recommended to retain the current settings are as follows:

- ❑ 6-hour look-ahead
- ❑ Korean uplift algorithm (retain and monitor)
- ❑ Current mark-up methodology
- ❑ RR modelling methodology

9.4 Confidential data and models supplied

This report is supplied to the RAs with two versions of the validated PLEXOS model 2019-2025:

- A version for the RA's including confidential data provided by market participants such as VOM costs and start costs
- A public model version with confidential data removed.

We are not able to publish all of the data gathered and used. We would therefore suggest that for start costs and VOM costs users make their own assumptions.

ANNEXES

A1 Backcast outcomes

A1.1 Monthly backcast price results

Table 16 Monthly average backcast price results

	Historical	RR-PLEXOS (New GB model)	RR-PLEXOS (Historical GB prices)
October 2018	€73.70	€70.38	€71.84
November 2018	€67.20	€67.30	€67.85
December 2018	€76.12	€70.53	€70.69
January 2019	€78.09	€72.79	€72.87
February 2019	€54.53	€53.83	€53.52
March 2019	€49.21	€51.49	€50.18
April 2019	€49.34	€48.97	€49.68
May 2019	€48.53	€43.34	€44.19
June 2019	€42.90	€38.40	€38.67
July 2019	€51.25	€42.38	€43.16
August 2019	€44.73	€39.04	€38.53
September 2019	€44.10	€39.81	€39.34
Average	**€56.64**	**€53.19**	**€53.38**

A1.2 Monthly backcast interconnector flow results

Table 17 Monthly backcast interconnector flow (to GB) results

	Historical	RR-PLEXOS (New GB model)	RR-PLEXOS (Historical GB prices)
October 2018	121 GWh	95 GWh	190 GWh
November 2018	181 GWh	163 GWh	238 GWh
December 2018	109 GWh	128 GWh	172 GWh
January 2019	89 GWh	117 GWh	146 GWh
February 2019	162 GWh	276 GWh	271 GWh
March 2019	156 GWh	236 GWh	189 GWh
April 2019	154 GWh	117 GWh	198 GWh
May 2019	126 GWh	225 GWh	274 GWh
June 2019	183 GWh	281 GWh	318 GWh
July 2019	89 GWh	248 GWh	298 GWh
August 2019	107 GWh	263 GWh	281 GWh
September 2019	123 GWh	205 GWh	212 GWh
Total	**1600 GWh**	**2353 GWh**	**2786 GWh**

Table 18 Monthly backcast interconnector flow (from GB) results

	Historical	RR-PLEXOS (New GB model)	RR-PLEXOS (Historical GB prices)
October 2018	244 GWh	233 GWh	99 GWh
November 2018	132 GWh	160 GWh	86 GWh
December 2018	284 GWh	224 GWh	173 GWh
January 2019	333 GWh	280 GWh	243 GWh
February 2019	140 GWh	73 GWh	76 GWh
March 2019	209 GWh	101 GWh	150 GWh
April 2019	181 GWh	182 GWh	113 GWh
May 2019	162 GWh	38 GWh	46 GWh
June 2019	97 GWh	13 GWh	25 GWh
July 2019	303 GWh	56 GWh	54 GWh
August 2019	246 GWh	39 GWh	83 GWh
September 2019	241 GWh	104 GWh	135 GWh
Total	**2572 GWh**	**1503 GWh**	**1283 GWh**

A2 Full recommendation summary

The full recommendation summary summarises the minor recommendations made throughout the report, and the major recommended model changes resulting from the validation exercises. For many of these minor recommendations there are additional activities which must be undertaken and/or additional data required before the recommendation can be actioned. These are described in the "Pre-condition" column. The "Priority" column provides an indication of the expected value of each activity to the improvement of modelled outcome.

Table 19 Full recommendation summary (including minor recommendations)

Area	Recommendation	Pre-conditions	Priority
Model start-time	Change start-time from 6am to 11pm	None	High
Model version	Update PLEXOS model version from 7.3 to 8.1	None	High
GB Modelling	Adopt new GB modelling approach	None	High
Wheeling Charges	Remove wheeling charges	None	High
Batteries	Review whether smaller batteries are likely to be dispatched in hourly DAM.	Improved data on proposed battery functions and contracts.	Low
Batteries/Storage	Review whether batteries and storage are primarily used for energy support or other services.	Improved data on proposed batter functions and contracts.	Medium
Supply/Demand Model inputs	Review whether model inputs can/should be changed to reflect DAM offered values.	2-4 additional years of market data. Development and maintenance of information sources relating gross demand, wind and embedded generation to offer/bid levels in the DAM.	Medium
Wind Modelling	Review the inclusion of separate offshore wind generation profiles.	Additional offshore wind generation build. Development of offshore wind profile data.	Low
DSU Pricing	Regularly review DSU pricing. Consider revising the spread of minimum income condition bids across multiple trading periods.	Additional DSU bid data.	Medium
Interconnector representation	Review whether improvements can be made on interconnector capacity calculations	1-2 years additional market data. System data relating to daily available capacity on interconnectors.	High
Uplift algorithm	Review whether Korean, SEM or a custom algorithm may best represent market results.	2-4 years additional market data.	Medium.
Scarcity pricing	Review whether scarcity pricing can/should be represented in the market model.	1-2 years additional market data. Offer data relating to days with observed elevated prices.	High
MIP	Review the impact of different simplification options on MIP solution quality and run-time.	None	Medium

Area	Recommendation	Pre-conditions	Priority
Assetless traders	Review whether assetless traders need to be explicitly incorporated into model.	2 years additional market data.	Low
Mark-ups	Review the inclusion of mark-ups in the model. Including considering: ▪ whether summer mark-up and uplift pricing is appropriate ▪ whether existing mark-ups should be retained, and ▪ whether a transparent mark-up creation methodology could be implemented.	2 years additional market data.	High