European Resource Adequacy Assessment

2025 Edition

ENTSO-E's proposal for ACER's approval

Annex 2 – Methodology

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1 Introduction to the European Resource Adequacy Assessment methodology

Adequacy studies aim to evaluate a power system's available resources and projected electricity demand to identify supply/demand mismatch risks under various scenarios. The focus of a pan-European adequacy forecast – as presented in the current European Network of Transmission System Operators for Electricity (ENTSO-E) report – is to assess the adequacy of supply to meet demand in the medium term time horizon while considering interconnections between different power systems across the European perimeter, as illustrated in Figure 1.

Figure 1: The interconnected European power system modelled in the ERAA 2025

The present European Resource Adequacy Assessment (ERAA) probabilistic methodology is considered a reference within Europe.

A large amount of detailed information is required to optimise and forecast a power system's operation. However, even with the best available data, the results are subject to considerable uncertainty and therefore result in a difficult decision-making process for market players.

Figure 2 illustrates the main elements of the ERAA 2025 methodology and their impact on adequacy. The adequacy assessment considers – among other factors – generation, demand, demand-side response (DSR), storage, and network infrastructure.

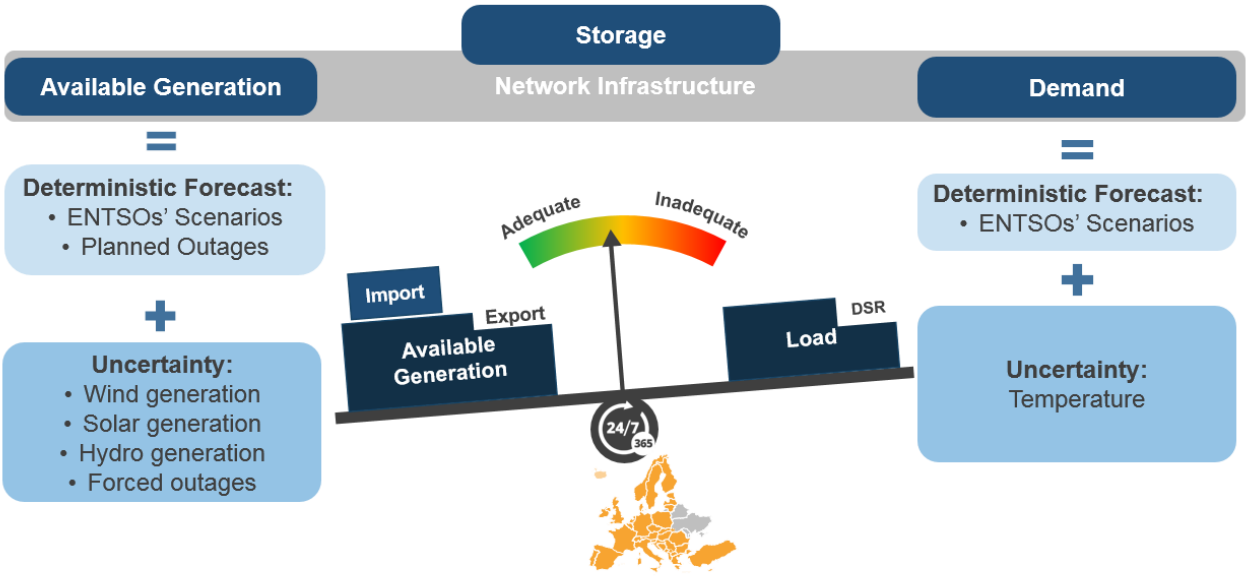

Figure 2: Overview of the ERAA 2025 methodological approach

1.1 Geographical scope and granularity

The present study focuses on the pan-European perimeter and neighbouring zones connected to the European power system. Zones are modelled either **explicitly** or **non-explicitly**. Explicitly modelled zones are represented by market nodes that consider complete information using the finest available resolution of input data (e.g. information regarding generating units and demand) and for which the unit commitment and economic dispatch (UCED) problem is solved (more details can be found in Section Unit commitment and economic dispatch11.5). Non-explicitly modelled zones are market nodes for which detailed power system information is not available to ENTSO-E. For these zones, exogenous fixed energy exchanges with explicitly modelled zones are applied.

Overall, study zones in 35 countries are explicitly modelled in ERAA 2025. The ERAA accounts for interconnections between study zones and intrazonal grid topologies. Some countries are divided into multiple study zones according to the market setting in those countries (e.g. Greece, Denmark and Italy). Table 1 to Table 3 provide a list of explicitly modelled, non-explicitly modelled, and non-modelled zones.

Table 1: Explicitly modelled countries / study zones

Explicitly modelled member countries/regions and study zones			
Albania (AL00)	Finland (FI00)	Republic of North Macedonia (MK00)	Serbia (RS00)
Austria (AT00)	France (FR00)	Malta (MT00)	Slovakia (SK00)
Belgium (BE00, BEO1)	Germany (DE00, DEKF)	Moldova (MD00)	Slovenia (SI00)
Bosnia and Herzegovina (BA00)	Greece (GR00, GR03)	Montenegro (ME00)	Spain (ES00)
Bulgaria (BG00)	Hungary (HU00)	Netherlands (NL00, NLOA, NLOJ, NLOK, NLOU, NLOW, NLLL)	Sweden (SE01, SE02, SE03, SE04)
Croatia (HR00)	Ireland (IE00)	North Ireland (UKNI,)	Switzerland (CH00)
Cyprus (CY00)	Italy (ITCA, ITCN, ITCO, ITCS, ITN1, ITS1, ITSA, ITSI, ITVI)	Norway (NOM1, NON1, NOS1, NOS2, NOS3, NOSF, NOWF)	United Kingdom (UK00, UKNI)
Czech Republic (CZ00)	Latvia (LV00)	Poland (PL00)	
Denmark (DKB2, , DKE1, DKN1, ,, DKW1)	Lithuania (LT00, LTH1)	Portugal (PT00)	
Estonia (EE00, EE01)	Luxembourg (LUG1, LUV1)	Romania (RO00)	

Legend:	*Onshore study zones*	*Offshore study zones*
Core FB Region	*Nordic Region*	*Other regions*

Table 2: Non-modelled countries/study zones

Non-modelled member countries/study zones	
Iceland (IS00)	Ukraine (UA00)
Türkiye (TR00)	

Table 3: Non-explicitly modelled countries/study zones

Non-explicitly modelled neighbouring countries/regions	
Morocco (MA00) – connected to ES00	Tunisia (TN00) – connected to ITSI
Ceuta (ESCE) – connected to ES00	Balearic Islands (ESIB) – connected to ES00
Egypt (EG00) – connected to GR00	

1.2 Time horizon and resolution

The ERAA target methodology aims to identify adequacy risks up to 10 years ahead and thus assists stakeholders in making well-informed investment decisions. ERAA 2025 considers the same number of target years (TYs) compared to ERAA 2024, i.e. four TYs (2028, 2030, 2033, and 2035). The choice of these four TYs is motivated by techno-economic trends and policy decisions relevant for the TYs assessed (e.g. the phase-out of certain generation technologies). Important trends relate to the phase-out of conventional generation technologies, the increased penetration of renewable energy sources (RES) and flexible assets (batteries, DSR, power to heat, etc.), and the increased electrification of energy demand.

An hourly simulation resolution – also referred to as an hourly market time unit (MTU) – has been adopted for all TYs and scenarios for the assessment. More information on the time resolution of each step can be found in Sections 10.4 and 11.1. Consequently, all input time series data for the UCED model are expressed in hourly intervals, e.g. RES generation, demand profiles, and net transfer capacities (NTCs). Data provided in a seasonal format by transmission system operators (TSOs) are transformed into hourly time series before being fed into the UCED model.

1.3 Modelling assumptions

The ERAA model is a simplified representation of the pan-European power system, which-, like any model ,is based on a set of assumptions. A non-exhaustive list of the main assumptions is provided below:

1) **Cost-driven dispatch decision:** The modelling tool dispatches available resources for specified time horizons by minimising overall system costs.
2) **Perfect foresight**: Available RES energy, available thermal capacities (accounting for planned maintenance and random forced outages (FOs)), DSR capacities, grid capacities (accounting for FOs), and demand are assumed to be known in advance with perfect accuracy, with no deviations between forecast and realisation. This also implies a perfect allocation of storage capacities (e.g. hydro storage) within the year.
3) **Demand is aggregated by study zone:** Individual end users or end user groups are not modelled.
4) **Demand elasticity regarding climate and price:** Demand levels are partly correlated with the weather. For example, temperature variations affect demand levels due to adaptations in the use of electrical heating/cooling devices. Part of the demand is modelled as explicit or implicit DSR, in which load can be reduced or shifted if energy prices are high (for more details, see Section 2.3.2). The remaining portion of energy demand is regarded as inelastic to price and will thus hold regardless of the energy price.
5) **Focus on energy markets only:** Only resources available to the market are accounted for in ERAA 2025. Adequacy is evaluated from a day-ahead (DA)/intraday market perspective. Lack of adequacy – the primary focus of the ERAA – should reflect the expectation that the system is not structurally balanced, at least during some hours and/or days. In addition, forward/futures markets or forward/futures contracts between market players are not modelled. As such, these do not influence modelled resource capacities.
6) **Non-market resources:** Non-market resources are considered a separate post-processing step of market simulations (e.g. strategic reserves).
7) **FOs only affect thermal generation and grid assets:** Power plants and grid assets are subject to FOs, which implies that their net generating capacity (NGC) is not continuously guaranteed.
8) **Planned maintenance of thermal units is optimised:** Planned maintenance of thermal units is scheduled in the least critical periods of the planning horizon, assuming perfect foresight of the demand and intermittent renewable infeed (i.e. periods likely to have a supply surplus rather than a supply deficit). The maintenance optimisation methodology further aims to reflect the impact of different climate conditions.

9) **Some technical parameters of thermal generators are modelled in a simplified manner:** Technical parameters considered as having a low impact on adequacy are modelled in a simplified manner or neglected (e.g. minimum uptime/downtime) on a pan-European scale.[1] Details are provided in Section 2.1.
10) **Flow-based (FB) modelling for the Core and Nordic areas:** In the adequacy model, grid limitations within the Core area (AT, BE, HR, CZ, FR, DE, HU, LU, NL, PL, RO, SK, ITN1, and SI) and Nordic area (eastern DK, FI, NO, SE) are modelled using the FB approach, which mimics multilateral import/export restrictions. The remaining part of Europe is modelled via bilateral NTC exchange limitations.
11) **''Copper plate model'':** The ERAA matches supply and demand – in addition to exchanges between study zones – without considering grid constraints within study zones.

1.4 General methodology changes compared with the previous ERAA

The ERAA is a deliverable that ENTSO-E has been mandated to carry out on an annual basis as described in the Electricity Regulation (2019/943). Each year, ENTSO-E aims to further improve the ERAA through various developments, offering insights that more accurately capture the complexities and evolving dynamics of the single electricity market. Improvements are developed while taking into account stakeholder priorities and feedback, through bilateral exchanges and public consultations.

This section highlights the developments that have been implemented in ERAA 2025, which differ from the previous ERAA edition, i.e. ERAA 2024.

Investor risk aversion
To account for investor risk aversion in the ERAA, hurdle premiums are introduced to capture risks associated with revenue distribution volatility as well as other elements, such as policy risks. The hurdle premiums together with the weighted average cost of capital (WACC) form the hurdle rates. In ERAA 2024, the hurdle premiums were calibrated on the Belgian electricity market and extrapolated to other markets. Based on ERAA 2024 analysis and prior edition results, it was determined that the distribution of revenues across the applied projected weather scenarios (WSs) revealed a particularly challenging risk profile. To allow for a more realistic investor risk-aversion modelling, it is deemed essential to account for revenue distribution information.

The ERAA 2025 introduces two risk aversion modelling approaches to reflect the uncertainty of investment decisions.

- The first approach includes enhanced hurdle premiums only for open cycle gas turbines (OCGT) and combined cycle gas turbines (CCGT) expansion candidates based on ERAA 2024 results to better reflect investor preferences under uncertainty, particularly for technologies with high exposure to price volatility.
- The second approach considers an enhanced hurdle premium combined with a revenue cap. This approach, in addition to the enhanced hurdle premiums for OCGT and CCGT, limits the expected revenues perceived by the investor during extreme price spike hours. This

[1] Yet, for some smaller systems, it may have an impact, and in cases like this National Resource Adequacy Assessments (NRAAs) is a valuable tool to complement ERAAs results.

ensures that revenue projections better reflect realistic monetisation potential under adverse conditions.

Together these two risk-aversion approaches account for the inherent uncertainty of investment projections within the single central reference scenario analysis. The adequacy risks in ERAA 2025 are presented as a range, with the lower bound corresponding to when risk aversion is characterised by a hurdle premium only and the upper bound corresponding to when risk aversion is characterised by both a hurdle premium and revenue cap.

The investor risk aversion modelling approach for ERAA 2025 is detailed in Section 10.10.

Weather scenario selection
In ERAA, uncertainty is integrated into the multiyear model through the introduction of WSs. The WSs represent three possible evolutions of climate, each with 12 weather conditions, resulting in a total of 36 different WSs. The economic viability assessment (EVA) uses stochastic optimisation to find a single optimal entry/exit decision of resource capacities for the set of possible WSs. However, the overall cost-based EVA modelling approach cannot be performed for the complete set of 36 WSs due to computational limitations. Therefore, the EVA is performed only for a subset of WSs to ensure computational tractability. The selected subset should be as representative of the complete set of WSs as possible to ensure consistency between EVA and economic dispatch (ED) adequacy modelling steps.

The subset of WSs is obtained through an optimisation process that aims to minimise the differences in the distribution of net revenues of thermal and DSR technologies between the subset and the complete set of WSs. In ERAA 2024, the process was performed based on preliminary ED results, i.e. ED performed on the National Trends and central assumptions scenarios for TY 2030. In ERAA 2025, the subset is selected based on the ERAA 2024 adequacy results, which improves the expected representativeness and consistency with respect to ERAA 2025 adequacy results. Additionally, the subset selection process accounted for all TYs and forced outage samples (FOSs) to further improve its representativeness. Furthermore, it should be highlighted that the subset of ERAA 2024 included weights, i.e. the weighted sum of the revenues of the selected subset was equal to the average revenue of the full set of WSs. In ERAA 2025, the approach aims to identify the most representative subset of equally weighted WSs, i.e. no explicit weights were applied.

The WS selection approach for ERAA 2025 is detailed in Section 10.5and an overview of this selection is provided in Annex 1.

EVA result transfer to ED
To keep the computational complexity of the cost-based EVA modelling approach tractable, generator units are aggregated at a nodal level based on their main characteristics: technology, fuel, and techno-economic parameters. This differs from ED adequacy modelling, which is performed on unit-by-unit data. An intermediate result transfer step is thus necessary to map the aggregated EVA outcomes to the unit-by-unit data.

In ERAA 2024, this result transfer was performed using a linear derating approach, i.e. the installed capacity of all units belonging to the same technology is derated homogeneously and proportionally to their installed capacity in the adequacy model. ERAA 2025 adopts a more granular and realistic approach by applying EVA outcomes at the individual unit level. Specifically, for decommissioning decisions, units with the lowest economic viability are prioritised for retirement. Units are sequentially decommissioned until the total capacity designated for decommissioning in the EVA is reached. To ensure the EVA targets are met precisely, any residual capacity that cannot be fully decommissioned through whole units is addressed by partially derating the final unit.

The EVA unit aggregation and result transfer to ED for ERAA 2025 is detailed in Section 10.6.

2 Model components and granularity

This chapter provides an overview of the different elements that are part of the power system model in ERAA 2025, their granularity and their characteristics.

2.1 Generation/resource side

Table 4 presents the categorisation and spatial granularity of the resource technologies considered.

Table 4: Classification of resource units

Category	Technology	Aggregation
RES	Wind	Aggregated in Pan-European Climate Database (PECD) zones; onshore and offshore wind capacities are collected and modelled separately
	Solar	Aggregated in PECD zones; solar photovoltaic (PV), rooftop solar PV, concentrated solar (thermal) with storage and concentrated solar (thermal) without storage are collected and modelled separately
	Other RES	Aggregated in study zones
	Hydro without reservoir: run-of-river (RoR) and pondage	Aggregated in study zones
	Hydro with reservoir: Reservoir, open-loop pump storage plants (PSP), closed-loop PSP	Aggregated in study zones
Non-RES	Coal	Unit-by-unit
	Gas	Unit-by-unit
	Lignite	Unit-by-unit
	Oil	Unit-by-unit
	Nuclear	Unit-by-unit
	Other non-RES	Aggregated in technology bands
Storage	Batteries	Aggregated in study zones
DSR	DSR	Aggregated according to price/duration
Hydrogen	Hydrogen-fired turbines	Unit-by-unit

Generation data are provided by TSOs through the Pan-European Market Modelling Data Base (PEMMDB). Climate-dependent data, such as hydro inflows, solar, and wind generation time series, are included in the PECD. Section 12 provides more information about the PEMMDB and PECD. Additional standard parameters are also collected by ENTSO-E, known as the common data (e.g. FO rates per technology).

2.1.1 RES

For wind, solar and other RES technologies, the total capacity installed at the PECD zone level is specified and corresponds to the sum of all plant-by-plant and aggregated capacities. In addition, hourly generation curves can be assigned to individual units and/or aggregated capacity provided by TSOs. Solar and wind generation are climate-dependent and result from solar irradiance and wind conditions, respectively (see Section 12.3). Planned outages and FOs for RES technologies are already included in the hourly time series and therefore are not explicitly modelled.

The available power of RES technologies is injected into the grid at no cost or curtailed following the optimisation model's decision.

The characteristics of hydro technologies – namely RoR, pondage, hydro with traditional reservoir, open-loop PSP and closed-loop PSP – are described separately in Sections 2.1.4 and 6.1.

Other RES aggregates small combined heat and power (CHP) units, waste incineration plants, non-dispatchable thermal generation, and other plants that use biofuels and cannot be provided in a unit-by-unit resolution.

2.1.2 Non-RES

The models only account for units available in the market. Thermal units are dispatched according to their marginal production costs and other plant parameters, including associated costs for CO_2 emissions. No CO_2 emissions are considered for biofuel units. In addition, start-up costs are considered when reporting and assessing costs associated with each unit, although they are not included in the optimisation when determining the optimal dispatch, as this would require introducing binary variables into the mathematical formulation of the optimisation problem, thus increasing its complexity. Table 5 describes the consideration of unit-specific technical parameters as modelled, non-modelled, or simplified modelling as applied in ERAA 2025. Technical parameters assumed to have a significant impact on resource adequacy are explicitly modelled or simplified due to computational complexity. Parameters that are less relevant or have no impact on resource adequacy are neglected in the simulation.

Table 5: Summary of various parameters in the models

Parameter	Description	Accounted in EVA and/or adequacy step
Heat rate [GJ/MWh]	Amount of energy used by a power plant to generate one MWh of electricity	Modelled in both steps
FO rate	Likelihood of an unplanned outage	Modelled in both steps
Must-run [MW]	Hourly constraint for a single or group of units to produce at least a certain amount of MW.	Modelled in both steps[2]

[2] Must-run profiles are not modelled for units with CHP profiles.

Min stable level [MW]	Minimal operation level of a unit	Not modelled
Derating [MW]	Hourly constraint for single or group of units to reduce the capacity offered to the market	Modelled in both steps
CHP revenue profiles [€/MWh_el/h]	Hourly profile by which the variable operations and maintenance (VOM) costs of the CHP unit are reduced	Modelled in both steps
Start-up time [h]	Time interval required to start a unit from 0 to a minimum stable level	Not modelled
Start-up cost [€]	Cost of starting a generating unit	Not explicitly modelled in optimisation, added in post-processing
Ramp rates [MW/h]	Limitation on the increase / decrease of the generation level within one hour for a unit that is already dispatched	Not modelled
Minimum up/down time [h]	Minimum time interval that a unit should be in / out of operation, frequently related to economic reasons	Not modelled

The impact of ramp rates and minimum up/down times on adequacy indices is negligible due to the perfect foresight assumption in the simulations. Scarcity situations are anticipated in advance, and units are ramped sufficiently early to cope with any adequacy risk and the associated high costs. Similarly, start-up times do not have a significant impact on adequacy results during normal operation due to the perfect foresight assumption. However, immediately after the FO of a unit and a subsequent scarcity, the availability of this unit may be further constrained by the start-up time, even under assumptions of perfect foresight. Nevertheless, as start-up time represents only a small fraction of the mean time to repair, its impact remains limited.

In addition to unit-by-unit thermal generators, other non-RES technology comprises multiple bands of aggregated non-RES technologies for each market node. Similar smaller plants are grouped together by technology, price, and efficiency, and can be given a must-run status. TSOs are free to provide a time series of aggregated capacity with an hourly derating profile, if relevant. Available capacity profiles can also be specified and provided for the different WSs. Available capacity profiles reduce computational complexity by simplifying unit dispatch for smaller plants, while still considering reduced power output from planned maintenance or FOs.

Other non-RES usually aggregate small CHP units, waste incineration plants, non-dispatchable thermal generation, and any other plants that use fossil fuels and cannot be provided in a unit-by-unit resolution.

2.1.3 Batteries

Battery storage is increasingly adopted to introduce flexibility into the grid. This flexibility can either participate in the market (e.g. ''in-the-market'' batteries) or not (e.g. ''out-of-market'' batteries (oomB)). All in-the-market battery capacity is ''price-elastic'' and explicitly modelled. Its dispatch is optimised within probabilistic modelling. The main parameters considered for this technology type are as follows:

- Installed output capacity (MW)
- Storage capacity (MWh)
- Efficiency (92% per cycle, or values provided by TSOs)
- Initial state of charge (default: 50%)

As described in Section 2.3.2, oomB are accounted as implicit DSR (together with electric vehicles (EVs) and heat pumps (HPs)) and can further be classified as either ''price-elastic'' or "price-inelastic". The former are explicitly modelled, while the latter are exogenously accounted for in the demand profiles based on information provided by TSOs. Open-loop PSP and closed-loop PSP storage technologies are described in the following section.

2.1.4 Hydro

Hydro capacities are aggregated by study zone and technology type. The availability of hydro energy inflows and additional hydro constraints, in addition to the criteria for capacity aggregation, is available and defined in the Pan-European Hydropower Modelling Database (also referred to as the 'PECD Hydro database'), complementing the PECD[3]. A key improvement in the hydropower modelling methodology for ERAA 2025 arises from the update of the PECD Hydro database, within which RoR and pondage were split into two distinct categories. This allows a clearer distinction between pure RoR and RoR with pondage capabilities, as well as small storage, as explained below.

Hydropower plants are now aggregated into five distinct technology categories:

1. RoR
2. Pondage
3. Reservoir (hereafter referred to as "traditional reservoir")
4. Open-loop PSP reservoir
5. Closed-loop PSP reservoir

The RoR category aggregates non-dispatchable hydropower (river) plants whose generation profile follows the contingent availability of natural water inflows with negligible modulation capabilities.

The new pondage category – now separated from the pure RoR – instead collects fluvial or swell power plants with pondage capabilities, i.e. the possibility to leverage a dam or storage system ahead of the turbine inlet and thus leverage a certain degree of generation flexibility with respect to the natural water inflows. The pondage category also accounts for small daily storages, i.e. small reservoirs without pumping capabilities and with a ratio of reservoir size (MWh) to NGC (MW) of less than 24 hours.

Major hydro storage plants without pumping capabilities are instead merged into the traditional reservoir category. PSPs are differentiated between basins with natural inflows, i.e. open-loop PSP reservoirs, and PSPs without natural inflows, i.e. closed-loop PSP reservoir.

Hydropower generation is governed by a set of constraints and parameters that define the maximum power available for turbine (or pumping) operations, including hydro natural inflows, minimum and maximum generation, and reservoir level constraints. Due to the level of aggregation

[3] Hydropower modelling - New database complementing PECD

– i.e. aggregated capacity per technology type – FOs and maintenance requirements are implicitly reflected in the time series defining the maximum generation constraints. The data availability varies depending on the set of input data provided by TSOs for the specific generation mix of the market nodes within their control areas. It follows that the data in Table 6 are not fully available for all market nodes but rather indicate the template and structure of the database itself.

Table 6: Key hydropower data and constraints aggregated per technology type

MW / GWh	RoR	Pondage	Trad. reservoir	Open-loop PSP	Closed-loop PSP
Hydro inflows	D	D	W	W	-
Max. power output	D	D	W	W	W
Max. generated energy	D*	-	W*	W	W
Max. pumping power	-	-	-	W	W
Max. reservoir level	-	D*	W*	W*	W*
Min. reservoir level	-	D*	W*	W*	W*
Reservoir size	-	Y	Y	Y	Y
Turbine capacity	Y	Y	Y	Y	Y
Pump capacity	-	-	-	Y	Y
Size/capacity ratio [h]	-	≤ 24	>24	any	any

D: Daily	W: Weekly	Y: Yearly	-: Not applicable	■: Not modelled	* : Not modelled in EVA

Following is a detailed description of the modelling assumptions and the hierarchy of the constraints collected in the table above.

Hydro inflows – available as cumulated daily or weekly energy lots – are equally distributed over 24 or 168 hours, respectively, given the hourly resolution of the UCED simulation. Depending on the hydropower category, inflows are immediately dispatched (e.g. pure RoR generation) or stored within the hydro reservoirs and released according to the optimised reservoir management performed by the modelling tool. If available hourly inflows exceed the dispatch needs or the maximum reservoir level trajectories, the modelling tools can decide to spill (i.e. dump) the inflow surplus.

Maximum generation power constraints regulate the hourly hydropower dispatch. If not explicitly provided, maximum generation is set to be equal to total installed capacity, derated by the frequency containment reserve (FCR) and frequency restoration reserve (FRR) hydro reserve requirements, if applicable. RoR generation is assumed to be non-dispatchable by definition, and thus daily inflows are turbined at a constant hourly output during the day. If a non-zero reservoir size is provided for the pondage category, such dispatch flexibility is granted according to maximum generation profiles, which can reflect both the non-dispatchable RoR and the dispatchable swell or pondage share of the aggregated capacity, respectively.

Maximum generated energy constraints represent weekly limitations to the energy output that are enforced in an intertemporal manner, i.e. the total generation over the whole week must be lower than the maximum energy constraint for the respective week. These types of constraints can be retrieved from a detailed analysis of historical generation profiles, reflecting the combination of a wide range of restrictions, including maximum water flows from/to reservoirs or river damns due to environmental regulations; regulated levels of river or hydro storage flows due to regulated water use for navigation, agriculture, or others uses; technical operational constraints of cascade reservoir systems and PSP plants; and any other constraints specific to a given study zone.

Reservoir level constraints are treated as discrete constraints to be enforced by the modelling tool at the beginning of each week, i.e. during the first hour of the week. Nevertheless, the intrinsic complexity of optimising hydropower generation from hydro reservoirs characterised by climate-dependent and/or seasonal constraints and inflow patterns might sometimes lead to punctual infeasibilities in the UCED solution. Such infeasibilities frequently arise from the solver attempting to enforce the initial reservoir level (or minimum/maximum level) as hard constraints at the beginning of each week without sufficient flexibility. Therefore, two sets of minimum and maximum reservoir level constraints are collected.. The constraints represent historical minimum and maximum measured (weekly or daily) levels, as well as technical constraints such as operational limits of the reservoir that are independent from climatic conditions, e.g. safety operational levels, minimum water reserves for potable and agricultural uses, and others, which can never be violated. When infeasibilities or adequacy issues are detected, the solution adopted is to treat the reservoir level trajectories as soft constraints, thus allowing the solver to violate them at a high penalty cost. Setting the penalty cost sufficiently high but still lower than the value of lost load (VoLL) ensures that the solver prioritises the dispatch of hydro resources and inflows during hours of generation scarcity to avoid energy not served (ENS) if potentially in conflict with reservoir level trajectories.

Maximum pumping is treated analogously to maximum power output constraints.

2.1.5 Balancing reserves

Balancing reserves are power reserves contracted by TSOs that help stabilise or restore the grid's frequency following minor or major disruptions due to unforeseen factors such as outages (generation or interconnection) or rapid demand changes. For each study zone, an amount of capacity equal to the total upward FCR and FRR capacity must be withheld from the energy-only market (EOM).

For ERAA 2025, TSOs could choose to account for balancing reserve requirements by thermal, renewable (wind and solar), explicit DSR, batteries, and/or hydro (reservoir, open-loop PSP, and closed-loop PSP) units. For thermal units, known contracted capacities for reserves could already be deducted from the data reported by the TSOs. TSOs were also able to report FCR and FRR requirements that must be explicitly modelled and covered by the remaining available thermal and/or renewable fleet. These requirements are not already accounted for in the reported NGC. Section 9 provides further insights into how the adequacy models account for reserve requirements.

2.2 Grid side

TSOs provide static or hourly forecasts of available NTC. This data is categorised by high voltage alternating current (HVAC) and high voltage direct current (HVDC) technologies, with NTC values aggregated at the border level. Planned maintenance for transmission lines is integrated into the NTC hourly availability, as provided by TSOs. Transmission levels depend on deterministic planned outages and random FOs, which are modelled in the same manner as for dispatchable generation resources. TSOs can report a specific forced outage ratio (FOR) per interconnector. Standard assumptions of 0% for HVAC and 6% for HVDC are applied if TSOs do not provide specific FOR values. Interconnectors between market zones can comprise multiple poles, which are also explicitly modelled in the ERAA. For ERAA 2025, the default assumption has been one pole per line for interconnectors, if no data has been provided.

Due to the complexity of power systems, the consideration of multilateral interconnection restrictions – such as flow-based market coupling (FBMC) – becomes more important. Therefore, FBMC is implemented for two capacity calculation regions (CCR) the Core region, which covers Central Europe, and the Nordic region, which covers the Nordic countries. This is elaborated in Section 4.

2.3 Demand and flexibility

Most of the domestic demand is fixed and unaffected by endogenous market prices, making it inflexible. However, a portion of the demand is flexible and represented through explicit or implicit DSRs. Implicit DSR includes the price-sensitive share of non-market demand side resources (EVs, HPs, and household batteries). Table 7 summarises the above.

Table 7: Modelling of explicit and implicit DSR

	Examples	In the market?	Price-sensitive?	Modelling choice
Explicit DSR	Industrial DSR	Yes	Yes	Explicitly modelled
Price-sensitive implicit DSR	EVs, HPs, household batteries (oomB)	No	Yes	Explicitly modelled

Constraints on the maximum daily operating hours for DSR and the activation time of implicit demand side response (iDSR) are included in the EVA and UCED.

2.3.1 Base demand

The base or inflexible demand comprises any fixed load and includes as separate components the price insensitive parts of EVs and HPs, optionally beyond the meter rooftop PV and batteries. The latter component would reduce the total net demand from a grid perspective.

TSOs can choose to either have ENTSO-E calculate the base demand time series on their behalf based on data they provide or provide the time series themselves. ENTSO-E generates demand time series using a dedicated tool, i.e. the Demand Forecasting Toolbox (DFT).

2.3.2 Price-sensitive demand-side flexibility

The categories belonging to "price-sensitive" DSR are explicit DSR and price-sensitive implicit DSR.

Explicit DSR capacity differs between study zones and hours of the day. The dataset provided by the TSOs includes:

- the maximum DSR capacity [MW];
- the DA activation price [€/MWh];
- the actual availability [MW] for all hours of the year; and
- the maximum number of hours for which the DSR source can be used per day (default: 24 hours).

Each of the above parameters can be specified for different activation price bands, as either a market resource or strategic reserves (the latter is only considered in the ERAA adequacy simulations as a post-processing step, and if resources are already contracted and approved in the respective TY). From a modelling perspective, DSR is similar to any other generation asset, albeit with an activation price that is typically higher than the marginal cost of most other generation categories and with an availability rating that limits activated DSR capacity for a given hour.

The approach for the iDSR implemented in ERAA 2025 aims to explicitly include the flexibility – with respect to endogenous market prices – expected from EVs, HPs, and oomB in the market models (with due simplifications). An important input for this modelling approach is the share of price-sensitive consumers $\boldsymbol{R}$ among these consumer types. These vary between countries and are collected from each TSO as a best estimate. Based on this parameter, we can compute the amount of price-sensitive EVs, HPs, and oomBs.

The price-sensitive share of oomBs is included in the market model as a battery characterised by **installed charge/discharge capacity** and **storage size** (as directly reported in the data collected for oomB capacity) multiplied by the corresponding price-sensitive ratio $\boldsymbol{R_{oomB}}$. The example below illustrates the application of $\boldsymbol{R_{oomB}}$.

Assuming for a given study zone and TY:
- an oomB installed capacity of 350 MW;
- a storage capacity of 1,100 MWh; and
- a $\boldsymbol{R_{oomB}}$ of 5%.

The following would be explicitly modelled:

- **Charge/discharge capacity** = Capacity x R_{oomB} = 350 MW x 5% = 17.5 MW
- **Storage size** = Size x R_{oomB} = 1,100 MWh X 5% = 55 MWh

In addition, the following assumptions are made:

- **State of charge (SoC)** initial and final level of the year = set to 50% by default
- **Cycle efficiency** = set to 92% default value

For EVs and HPs, the methodology primarily leverages the demand forecasts generated by the dedicated tool, as described in the previous section, which includes a base consumption for EVs and HPs. In the modelling tool, the price-sensitive share of EV and HP consumers ($\boldsymbol{R_{EV}}$ and $\boldsymbol{R_{HP}}$) can shift their demand within time windows to gain arbitrage and improve resource adequacy in times of scarcity. The energy within each time window must be balanced, i.e. energy cannot be shifted outside a time window.

Table 8 presents the start times of the time windows applied for EVs and HPs depending on the respective time zone (all times UTC). For HPs, there are four time windows per day, each covering six hours, while for EVs there are three time windows with two windows each covering six hours and an extended nighttime window covering 12 hours. The underlying assumption for the extended nighttime EV window is that most EVs are connected to the grid and not in driving mode at night. The detailed mathematical formulation of the modelling of flexible EVs and HPs can be found in Appendix 2.

Table 8: EV/HP time windows

Time zone	Start time 1	Start time 2	Start time 3	Start time 4
STANDARD (UTC)	-/5 am	7 am/11 am	1 pm/5 pm	7 pm/11 pm
UTC+1	-/6 am	8 am/12 am	2 pm/6 pm	8 pm/12 pm
UTC+2	-/1 am	9 am/7 am	3 pm/1 pm	9 pm/7 pm
UTC-1	-/4 am	6 am/10 am	12 pm/4 pm	6 pm/10 pm

3 Overview of scenarios and calculations steps

This section provides an overview of the ERAA adequacy assessment process, which starts with collecting a large amount of raw input data processed to serve as input for the scenario computations. Preparing input data for all TYs and uncertain variables (e.g. WSs) is a major task for ERAA 2025. Figure 3 presents the following elements:

- The data are stored/generated in three databases/tools, namely the PEMMDB, PECD, and DFT and constitute the National Trends scenario. For more information, see Annex 1.
- Some data are defined by TY, whereas other data are defined by WS (*N* WSs) or both TY and WS.
- A single modelling tool is used to optimise planned maintenance profiles for the thermal generation assets of each modelled market node (for unplanned maintenance, see Section 11.4). Planned maintenance of grid assets is already included in the NTCs provided by the TSOs.
- Thermal capacity can be dispatched at will, whereas wind and PV capacities depend on weather conditions during their operation. As such, the available wind and PV (power) generation can be injected at no cost (or curtailed following the optimisation model's decision).
- The datasets are fed into the reference market modelling tool, which is further described in Figure 4. First, the input data and assumptions are fed into the EVA model to assess how likely generation capacities are to be retired, invested in, (de)mothballed, and/or extended in lifetime. Next, the EVA entry/exit of market capacity is included in the central reference scenario, followed by the adequacy assessment through a Monte Carlo (MC) simulation to produce adequacy metrics.

National Trends Input calculation process

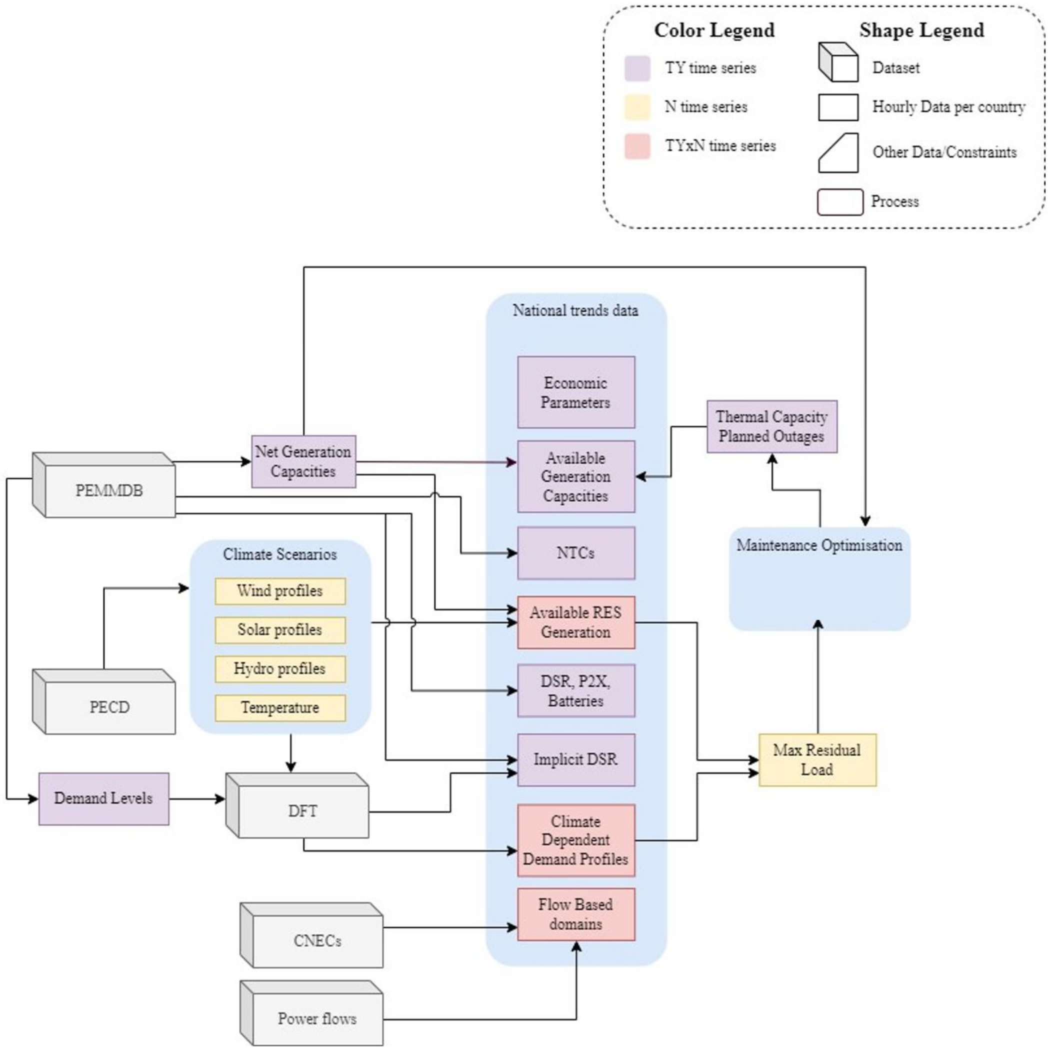

Figure 3: Overview of initial input data processing

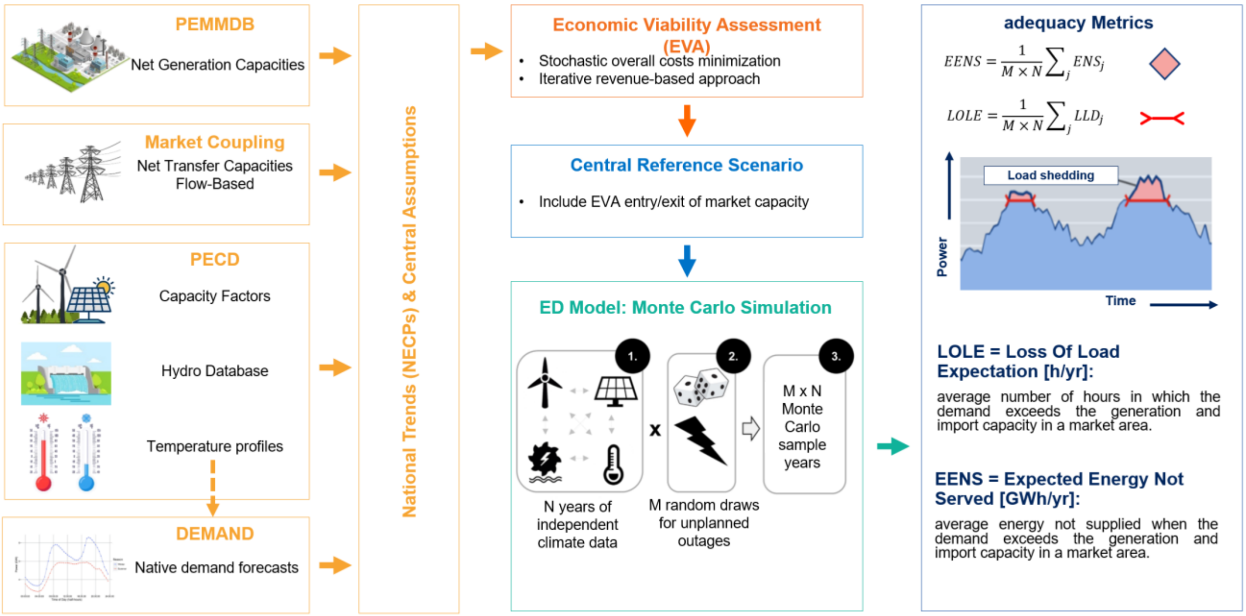

Figure 4: Multi-step ERAA approach

4 Flow-based domains calculation methodology

The ERAA target methodology requires implementing, where applicable, FB capacity calculation methodology (CCM) for cross-zonal trade. In the European DA market for electricity, energy is traded within and across study zones. The market assumes no grid restrictions within a study zone, although there are limitations to the amount of energy that can be traded across study zones. One approach to accounting for these limitations is market coupling by NTC, in which the trades across any given border and market time unit do not affect exchange capacities on other borders in the market clearing process. By contrast, the FBMC approach considers interdependencies in the power system by allowing export from or imports to the study zones as long as monitored network elements are not overloaded, thus better representing the physical reality of the grid. The market coupling approach is currently defined by CCRs[4].

Figure 5 shows the perimeter of the Core and Nordic regions, on which FB domains were calculated. Besides FB regions themselves, you may also see neighbouring systems that are considered through advanced hybrid coupling (AHC). Compared with ERAA 2024, northern Italy[5] was included in the Core FB region, and Switzerland is now considered through AHC.

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[4] https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32015R1222 , https://www.entsoe.eu/network_codes/ccr-regions/

[5] Northern-central Italy is considered through AHC. Southern-central Italy and southern Italy are considered through AHC as they are connected to northern Italy in 2030 and 2035, respectively.

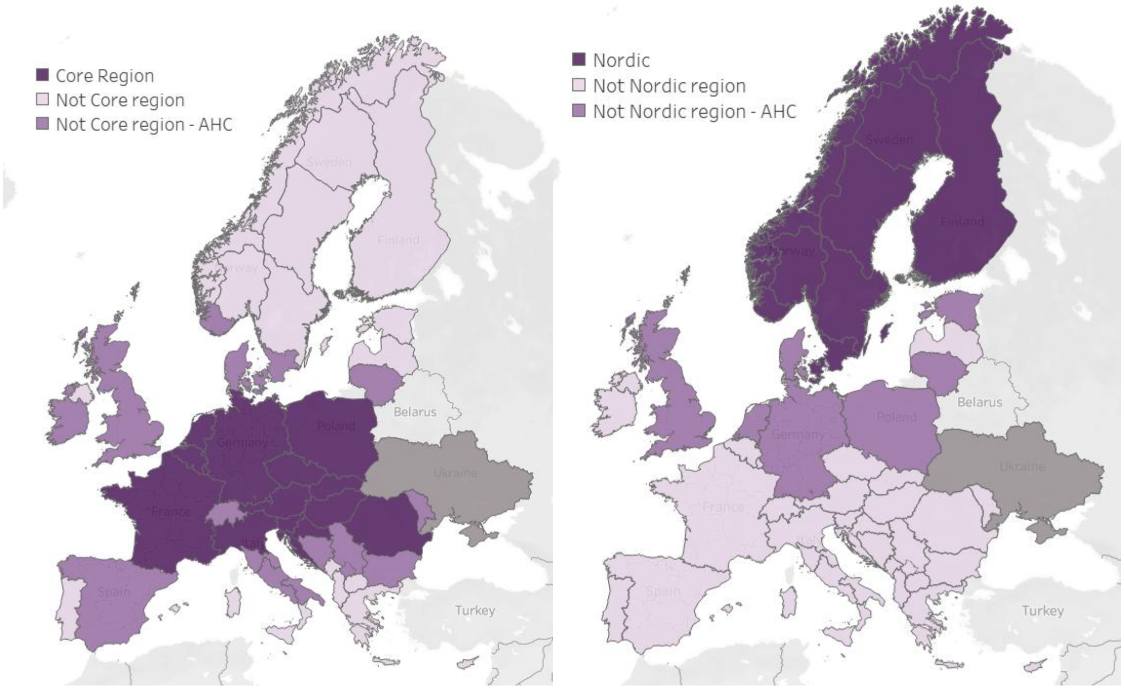


Figure 5: Core (left) and Nordic (right) flow-based market coupling region

4.1 FB domain concept description

In broad terms, a FB domain describes the solution space for the net positions of individual study zones in a given CCR for a given MTU. In other words, it defines the limitation for exchanges between study zones in that CCR. It also enables accounting for external flows (to neighbouring countries) or internal direct current (DC) line flows.

A FB domain is defined by a set of linear constraints derived from linearised equations in the network models (analysing active power flow) across monitored network elements. A change in study zone net position directly translates into the power flow change on the respective network element. This relation is represented by power transfer distribution factors (PTDFs).

Monitored network elements considered critical network elements (CNEs)[6] in the capacity calculation are restricted to cross-border elements only. By including relevant contingencies – comprising both cross-border and internal network elements – the N-1 security constraints of the grid can be represented. This results in a list of CNECs, i.e. a list of CNEs combined with relevant contingencies under which particular CNEs are monitored. For each CNEC, a margin available for cross-zonal trade (MACZT) is defined, which restricts the power flow on the CNEC. This in turn will be the limiting factor for net positions of study zones in the form of FB domains.

As explained above, the constraints of a FB domain are given by the CNEC power transfer flow definition on the left-hand side, and their respective capacity margin on the right-hand side. Thus, a FB domain comprises linear constraints in the form of inequalities. In the conceptual FB domain provided in Table 9, there is a linear constraint in which *A, B,* and *C* correspond to the net positions

[6] ACER Decision on the Core CCR TSOs' proposals for the regional design of the day-ahead and intraday common capacity calculation methodologies

of study zones or flows and/or set points of selected external flows to the CCR, internal HVDCs, and selected phase-shifting transformers (PST) within the CCR:

$$-0.3A + 0.25B + 0.1C \leq 150 \text{ MW}$$

In FB with standard hybrid coupling (SHC), A, B, and C correspond to the net positions of CCR study zones A, B, and C with respect to the other study zones included in the CCR. However, these variables can also refer to setpoints of selected external flows into the CCR (AHC), the setpoints of HVDCs internal to the CCR (evolved flow-based, EvFB) and selected PSTs within the CCR. Whereas in SHC, the FB domain only models the impact of exchanges between CCR study zones on CNECs, in AHC, the impact of the interconnectors between CCRs is added to the model. The PTDFs (−0.3, 0.25, and 0.1 in this example) for AHC borders refer to the sensitivity of the flow on a CNEC to a change in flow over this AHC border. In EvFB, similar to AHC, the sensitivity of CNEC flow to setpoints of DC elements within the CCR is considered.

With the resulting set of constraints, the market simulation model can set the CCR net positions, the setpoints of DC elements, and the bilateral exchanges over non-Core borders while respecting the maximum flows allowed on all CNECs. Note that while the NTC constraints between CCR study zones are completely replaced by FB constraints, NTC values remain constraining for the maximum flows over the AHC elements themselves.

Table 9: Conceptual FB domain example

Critical network element	Contingency	Critical network element and contingency	Influence of the net position on the flow on each line (PTDF matrix)			MACZT (MW)
			A	B	C	
Line 1	None	CNEC 1	−30%	25%	10%	150
	Contingency 1	CNEC 2	−17%	35%	−18%	120
	Contingency 2	CNEC 3	15%	30%	12%	100
Line 2	None	CNEC 4	60%	25%	25%	150
	Contingency 3	CNEC 5	4%	-15%	4%	50
…	…	…	…	…	…	…

The constellation of non-redundant constraints can be described as a “convex hull”, forming an n-dimensional polytope. The dimensions correspond to the columns of the FB domain matrix. In the example in Table 9, the dimensions are given by A, B, and C.

To visualise a domain or compare between different domains, it can be useful to project the polytope onto a two-dimensional plane, which is comparable to casting the shadow of a three-dimensional object onto a wall. However, the computational complexity of creating the projection increases with the number of dimensions, as it requires enumerating the vertices of the full polytope.

When referring to the two-dimensional projection of an FB domain, the polygon displayed shows all admissible values for the two dimensions considered, but it does not show the implication of these values on the variables of the remaining dimensions. As an example, we assume a simplified three-dimensional domain with the shape of a cube as described in Table 10. Its projection onto the dimensions A and B, shown in Figure 6, makes it clear that this assignment forces C to adopt a net position of 0 in this example.

Table 10: Cube-shaped FB domain

CNEC ID	A	B	C	RAM
‘1	1	1	1	1
‘2	1	1	−1	1
‘3	1	−1	1	1
‘4	−1	1	1	1
‘5	1	−1	−1	1
‘6	−1	−1	1	1
‘7	−1	1	−1	1
‘8	−1	−1	−1	1

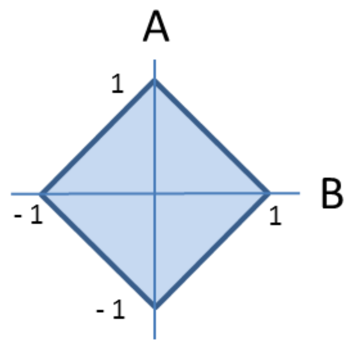


Figure 6: Two-dimensional projection of cube-shaped domain for C = 0

4.2 FB domain computation steps for Core CCR

The process of computing the Core FB domains can be summarised in six steps, as illustrated below:

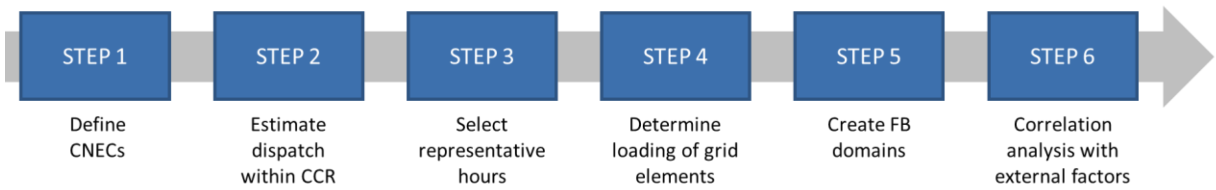


Figure 7: Steps for computing sets of FB domains for TY 2028

4.2.1 CNECs definition (Step 1)

In the first step, a list of CNECs that potentially limit cross-zonal trade is defined. As mentioned above, a CNEC is a combination of a CNE with a contingency that refers, for example, to overhead lines, transformers, or underground cables.

4.2.2 Computation of initial market dispatch within CCR (Step 2)

The hourly market dispatch within the studied CCR, in addition to exchanges with study zones outside of but connected to a given CCR, is computed and given to the grid model as an initial market dispatch to perform load flow analysis and compute FB domains.

4.2.3 Selection of representative hours (Step 3)

Given that calculating FB domains is computationally intensive, it is impractical to calculate for each hour of each WS of the initial market simulation. To overcome this limitation, a selection of representative hours from the input market study is made, on which FB domains will be calculated.

The selection of representative hours is based on a clustering process and provides a set of statistically representative, differentiated timestamps to calculate domains that are both meaningful (representative of a sufficient number of hourly situations) and different (to provide a wide range of possible network constraint situations).

The clustering is based on the hourly flows on the monitored CNEs without contingencies, which are a good proxy of the final shape of the FB domains. The clustering process is as follows:

- A load flow simulation is run on a representative grid model for each hour of the selected WSs, considering the initial market dispatch computed before, i.e. ERAA 2024 results. Consequently, the hourly flows on CNEs are computed (without simulating contingencies).
- The optimal number of clusters and the clusters themselves are computed based on the flows on CNEs, using a k-medoid clustering approach (see below for details). This identifies the representative hours across the selected WSs on which the FB domains will be calculated.

The optimal number of clusters is selected based on the computation of two clustering statistics, namely the total within sum of squares (WSSs) and the silhouette. These indicators are calculated for different numbers of clusters to determine the optimal number, maximising the consistency within one cluster and the difference between clusters. This led to the selection of three clusters for winter hours and three for summer hours, resulting in four FB domains to be computed.

A simplified FB domain is also computed based on a single representative time stamp for summer hours and for winter hours (each). This simplified FB domain is not a subset of the full FB domain described above.

4.2.4 Reference loading of grid elements (Step 4)

The reference loading of grid elements is calculated for a representative time stamp by performing a load flow calculation on the input grid model.

4.2.5 FB domains computation (Step 5)

Step 5 describes the computation of the FB domains for each representative hour, identified in Step 3. The FB domain calculation begins with the PTDF matrix, which is derived from the grid model and allows for linear power flow calculations. The PTDF matrix represents all changes to flows over the CNECs in response to injections in individual network nodes in the detailed grid model. This PTDF matrix provides nodal granularity and incorporates all network nodes represented by columns. A generation shift key (GSK) is required to allow for a zonal representation in accordance with the European study zone configuration. The GSK is a matrix that carries information regarding how the nodal power injection changes if the net position of a study zone moves up or down. Multiplying the nodal PTDF and GSK matrices results in a zonal PTDF matrix. Finally, the matrix is augmented by columns representing either DC links or exchanges with external CCRs that are modelled as ARC. In concrete terms, this means that PTDFs are calculated for each CNEC for each represented DC link (currently the Alegro and Piedmont–Savoie HVDC links) and for NTC borders between a Core and a non-Core study zone. This enables capturing the sensitivity of CNEC flows within the Core region to the flows on the represented DC links and the NTC borders between Core and other CCRs. This step concludes the left-hand side of the FB domain constraints (PTDFs).

To establish the right-hand side of the constraints (remaining available margins (RAMs)), the MACZT for each CNEC must be known. Its size depends on the physical active power transmission capacity, the base or “reference-flow” loading, and the flow reliability margin of the CNEC, as well as the minimum legal requirements for cross-zonal trade. Step 5 also includes a non-costly remedial action optimisation through PSTs, aiming to increase the size of the domain in its narrower dimensions. The outcome of this step might therefore differ depending on the actual constraining CNECs, which are linked to the CNEC list used to build the domain.

Once zonal PTDFs and RAMs have been computed for each CNEC, post-processing is performed to adjust RAMs to comply with the 70% requirements. The 70% regulation (Regulation 2019/943, Article 16) prescribes a minimum margin of the physical cross-border capacity that must be made available to cross-border trade. For this purpose, first the net positions of all study zones (within and outside of the Core region) are set to 0 (using the PTDFs previously calculated), and for each CNEC, it is checked whether the resulting flow is lower than or equal to 30% of the RAM of the CNEC. If this is not the case, the RAM is increased until the flow in this situation reaches 30% of the RAM for all CNECs.

This process within the FB domains computation methodology ensures that the Core domains computed are compliant with the 70% rule.

As the final part of Step 5, post-processing of the FB domains can be adopted for better handling. For this, an algorithm to reduce the number of (pre-solved) FB constraints is applied to identify and remove the constraints that have a negligible impact on the FB domain.

This is achieved in an iterative procedure as follows:

1. For each FB constraint cx in the given FB domain, quantify the impact of removing it, as a product of min/max net position ratios (before and after removal of cx).

$$Domain\ Impact\ (cx) = \prod_{\forall zone} \frac{NP_{zone}^{max}(with\ cx)}{NP_{zone}^{max}(without\ cx)} \cdot \prod_{\forall zone} \frac{NP_{zone}^{min}(with\ cx)}{NP_{zone}^{min}(without\ cx)}$$

2. Remove the FB constraint that has the lowest domain impact.
3. Repeat Steps 1 and 2 until the lowest FB domain impact becomes non-negligible (higher than a tolerance of 1%).

The aforementioned procedure can be used to reduce the number of constraints with a negligible impact on accuracy. This significantly reduces complexity and shortens computation times.

4.2.6 Defining when each FB domain should be used (Step 6)

Step 6 defines the final part of the FB methodology and describes how the FB domains computed are chosen for each hour in the adequacy assessment models.

First, a random forest classification algorithm is trained to identify conditions under which each FB domain is more likely to be representative. Total load and RES generation (solar, wind, hydro RoR generation) are considered as main conditions influencing FB domains, called determinants. Each determinant is considered at a study zone level. A large set of determinant data is built considering conditions in each hour of the cluster (identified in Step 3), which specific FB domain represents. With this dataset, the random forest classification algorithm identifies distinguished conditions under which each FB domain is representative.

Subsequently, to identify which FB domains should be chosen for every timestep of a prospective study, the trained random forest classification algorithm is applied for all possible conditions in a given prospective study. In this step, each time step of each WS is analysed by the algorithm considering determining conditions (total load, RES generation). By analysing the data, the algorithm, identifies which FB domain would best fit the conditions of that time step. The process is repeated for every time step of the prospective study.

4.3 FB domain computation steps for the Nordic CCR

The method for computing the Nordic FB domains follows a similar process, with a few differences that distinguish is from calculating FB domains in the Core region. The steps for calculating FB domains in the Nordic countries are summarised below.

4.3.1 Create a common grid model

In the Nordic CCR, each country develops and maintains a set of individual grid models of their control area for each TY. For TYs 2028 and 2030, all countries have updated individual grid models. For TYs 2033 and 2035 the process is simplified, with one grid model per country updated to represent both TYs, covering the most important updates to the grid. After preparing TY grid models, a common Nordic model is developed per TY as an input to subsequent market and power flow studies.

4.3.2 CNEC selection

After developing a common grid model, each TSO in the Nordic CCR models market and power flow outcomes to identify flow patterns and congestions to compile a list of CNECs for calculating PTDFs and RAMs, including cross-border connections. Note that each time the grid plan for a TY is updated, changing the topology of the common grid model, the list of CNECs must be recalculated. For ERAA 2025, CNECs are updated for all new grid models.

4.3.3 Update electricity market scenario modelling datasets

TSOs within the Nordic CCR collaborate to compile a list of input market assumptions for electricity demand and production in the Nordic area. This is undertaken in a scenario-based manner for each

TY. The continental European system is modelled with assumptions from Statnett's latest short term and long term market analysis (LMA 2024).

4.3.4 Calculate initial FB domains

The first step in calculating the FB domains is forecasting the marginal cost of water as an important input for forecasting the dispatch of hydro power in the Nordic CCR. This is completed using stochastic dynamic programming and then calibrated manually after verification through simulation. Next, the market dispatch is forecasted for 29 WSs. The market dispatch is solved in three-hour increments, giving 2,912 market outcomes and flow scenarios per climate year, a total of 84,448 computed initial RAM domains per TY. The grid model is used to calculate a static PTDF matrix for each TY.

4.3.5 Reduction of the initial domains

Measures are taken to reduce the complexity of the initial domains. The original 84,448 domains are reduced to a representative set of seven domains per TY. The representative sets are decided by creating seven clusters using k-means clustering, where each cluster represents a unique RAM domain. These FB domains are post-processed with a MACZT 20% of RAM requirement.

4.3.6 Assigning each hour to a cluster

ERAA climate year data (onshore wind, offshore wind, solar) is used to calculate hourly capacity factors. After computation of the seven final domains per TY, a nearest-neighbour algorithm assigns each hour of every ERAA WS to the cluster that best matches the calculated capacity factors. The resulting FB domain for each TY finally consists of seven unique domains, where each hour is assigned the most fitting of these domains.

4.3.7 Review and deliver FB domains for the ERAA

Finally, the FB domains are reviewed by checking the resulting power flows and power prices to ensure they are within reasonable expectations when compared to historical data.

5 Maintenance profiles calculation methodology

The main goal of periodic maintenance is to reduce the risk of unplanned unavailability of thermal capacity during potential times of scarcity – typically during periods of high load.

Hourly maintenance profiles for thermal units are calculated centrally by ENTSO-E for most study zones on a TY basis. If TSOs can provide better-informed maintenance profiles due to better knowledge of the specificities of their power system, these are considered in the models instead of central calculations. Maintenance profiles are calculated for each thermal generation unit for each TY. Maintenance of renewables, other non-renewables, and hydro-powered storage units is considered and reflected in the respective infeed and availability time series of these generators.

The objective of the ENTSO-E maintenance optimisation methodology is to maximise the available thermal capacity during potential times of scarcity. Using the annual planned outage rates[7] of each unit, maintenance outage periods are scheduled on a yearly horizon using an objective function aiming to level the weekly capacity margin[8] per market node. Levelling the capacity margin can be achieved as described in Figure 8, minimising the risk of ENS.

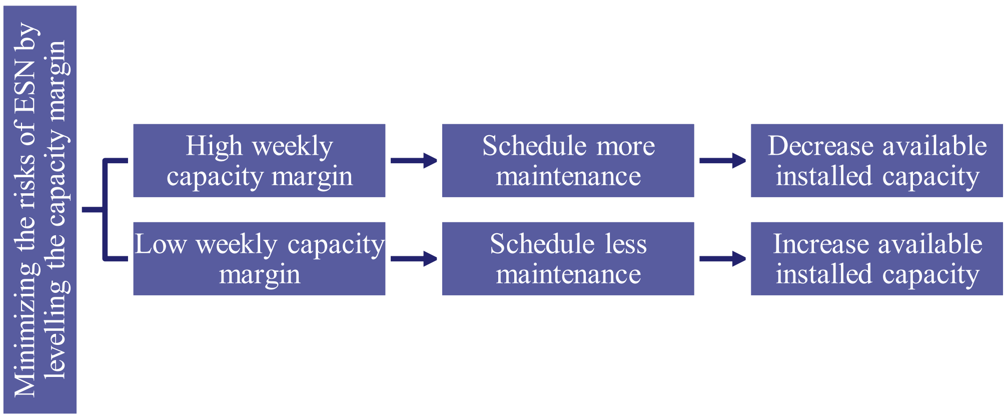


Figure 8: Levelling capacity margin with maintenance optimisation

The underlying load profile for maintenance planning is a residual load profile, as it is expected that producers will consider a certain level of renewable infeed when planning future maintenance. The load profile is obtained stepwise. First, a synthetic profile is computed by taking the minimum infeed of intermittent renewables over all WSs on an hour-by-hour basis. Subsequently, the latter is added to the hourly firm capacity of other generation units, as provided by the TSOs. Finally, the resulting profile is subtracted from the synthetic demand profile computed by taking the maximum native demand over all WSs on an hour-by-hour basis to yield the residual demand. This ensures

[7] Total number of days per year required for maintenance.
[8] Difference between peak load and available installed capacity during a given week.

that renewable infeed is accounted for to optimise the maintenance of thermal generation. The maintenance profiles are optimised on a country-by-country basis (in practice, cross-border interconnection capacities are not considered).

The resulting maintenance profiles – as determined by the above methodology – have been consulted with the respective TSOs. This allows the TSOs to amend and shape the maintenance profiles with specific knowledge not captured by the methodology.

Sections 10 and 11 provide more details on how these profiles are used in the EVA model and the adequacy model.

6 Long-term storage optimisation

The modelling tool performs a pre-optimisation step for large storage assets before the UCED optimisation. Available storage capacity is optimised so that energy is stored in times of sufficient supply and made available for discharging in times of higher demand and/or lower available generation. This pre-optimisation step occurs within the modelling tool at a coarser time granularity than the hourly UCED optimisation (described in Section 11.5), as the optimal management of storage resources requires much higher foresight and planning at a seasonal or even yearly level. In this (pre-)optimisation phase, the available energy in storage assets and any cumulated exogenous energy flows (e.g. natural inflows for hydro storages) are optimally pre-allocated in (e.g. daily) energy lots. As such, energy resources are saved and made available to each daily UCED sub-problem, minimising system costs, i.e. resource dispatch costs. The hourly dispatch of the energy available in storage assets is then finally optimised within each UCED sub-problem, starting from the pre-optimisation targets. These are refined and concretised into the final hourly generation based on the contingent availability of the other dispatchable and non-dispatchable resource capacities.

Consistent with the assumption of perfect market and non-opportunistic behaviour of market players, storage assets never set the marginal price when entering the merit order, but are rather dispatched as zero-cost resources that exploit marginal price gains by storing energy during hours at low(er) marginal prices (e.g. collecting inflows in hydro reservoirs or by direct power infeed through pumping or battery charge) and releasing energy during hours at high(er) marginal prices.

6.1 Hydro storage optimisation

Hydro storage represents the most complex element of storage optimisation. It is constrained not only by the hourly available generation capacity and storage capacity but also by the weekly reservoir level limitations. These constraints represent historical or technical minimum and maximum reservoir levels per week, as provided by TSOs. Figure 9 displays an example of minimum and maximum reservoir level trajectories, along with the initial and final reservoir levels, given as an input to the modelling tool.

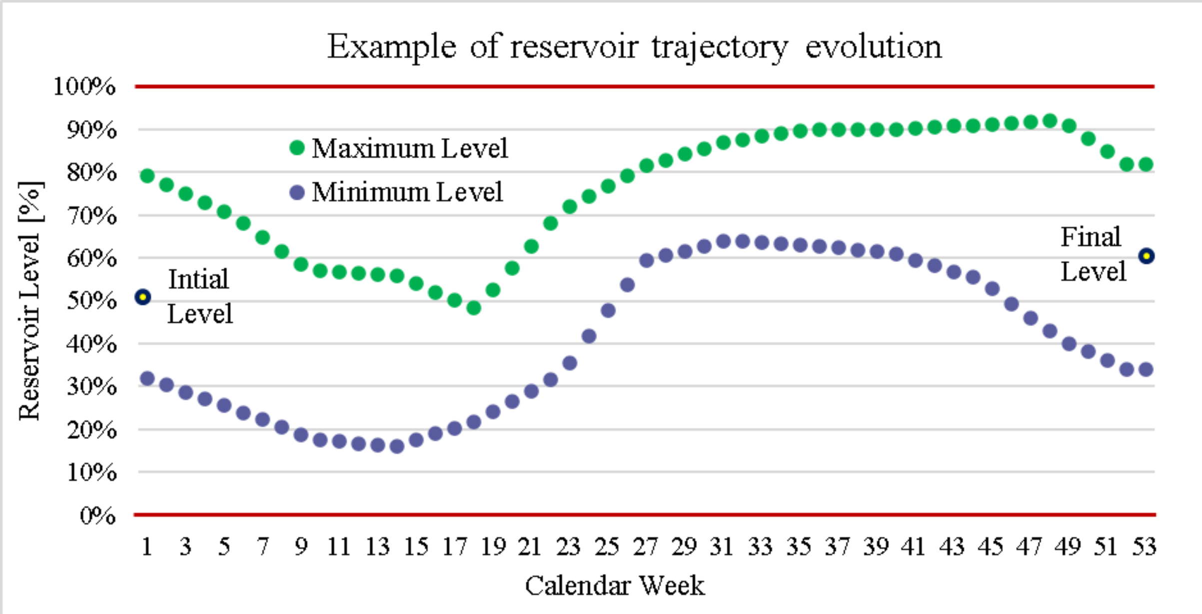


Figure 9: Example of reservoir trajectories and constraints

The initial reservoir level (WS specific) is taken as provided by TSOs. If not available, the average between the minimum and maximum level trajectory at Week 1 is taken. If both pieces of data are missing, 50% of the reservoir size is assumed as the standard value.

Consistently, the final reservoir level is taken as the fixed trajectory value at Week 52 or 53. If not available, the initial reservoir level of the following WS (e.g. WS 6 for the simulated WS 5) is selected. In the absence of fixed weekly reservoir levels, the average between the minimum and maximum level trajectory at Week 52 is taken. If all data for reservoir levels are missing, 50% of the reservoir size is assumed as the standard value.

In addition to reservoir level constraints, multiple additional parameters limit the operation of hydro power plants, as summarised in Table 6. The standard cycle efficiency (pumping–turbining) for PSPs is assumed to be equal to 75%.

In the EVA, due to computational complexity, a reduced set of hydro storage constraints is taken into account, as indicated in Table 6. Constraints with a limited impact on price formation and thus investment behaviour have been omitted.

6.2 Batteries

Battery data are provided by TSOs and – as described in Sections 2.1.3 and 2.3.2 – comprise in the market batteries (mostly large-scale) and oomB (mostly household). In-the-market batteries are price-sensitive and are explicitly modelled, while the price-insensitive share of oomB are exogenously included in the demand profiles based on information provided by TSOs, e.g. typical consumption pattern for household batteries.

The in-the-market capacities are aggregated by round-trip efficiency and modelled mainly using four parameters, namely charging capacity measured in MW, discharging capacity measured in MW, storage capacity measured in MWh, and round-trip efficiency in % reflecting the losses. The initial battery charge (at the start of the simulation) is assumed to be 50% of the storage capacity. The battery round-trip efficiency is modelled as charging efficiency. For example, a charging efficiency of 90% means that for 1 MWh taken from the grid, 0.9 MWh is stored in the battery and 0.1 MWh is lost. The discharge efficiency is assumed to be 100%. Hence, the storage capacity of the battery is the net capacity that can be utilised by the electricity system. This principle is illustrated in Figure 10.

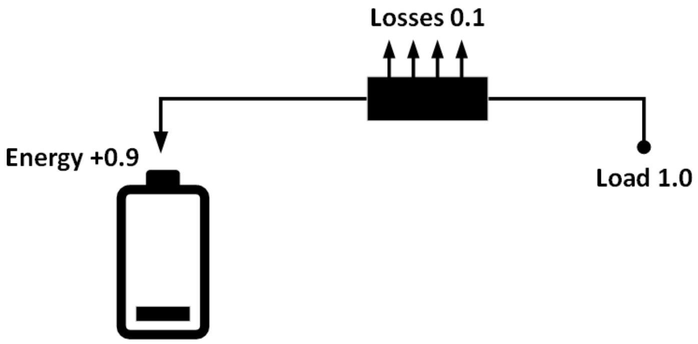


Figure 10: Illustration of the battery charging process

The energy off-taken from the grid by the batteries (demand) is valued at market price, whereas energy injected from the battery to the market is valued at zero cost (the cost is already covered by the charging). The overall optimisation target is to operate batteries to minimise total system costs, i.e. discharge at high electricity prices and charge at low electricity prices.

7 Sector coupling (P2X)

Electrolysers use the surplus electricity mainly generated in RES to produce hydrogen, which can then be used in various ways, e.g. as a fuel to re-generate electricity, in the transport sector, or for heat generation. Only the water electrolysis production process has been modelled in a simplified manner in ERAA 2025 as it is the only production method that relies primarily on electricity. The electrolysis units were modelled as an additional demand activated below a threshold price, defined in the equation below:

$$P_{act} = P_h * \eta * 3.6$$

where: P_{act} – electrolyser activation price [€/MWh]
P_h – hydrogen price[9] [€/GJ]
η – hydrogen production efficiency[10] [%]
3.6 – conversion factor MWh to GJ (1MWh = 3.6GJ) [MWh/GJ]

The adoption of such assumptions translated into the activation price of electrolysers in the range of 26.41–54.59 €/MWh depending on the TY and electrolysers' efficiency. Schematically, this principle is shown in Figure 11, illustrating that the electrolyser starts producing hydrogen if the price of electricity drops below the electrolyser activation price.

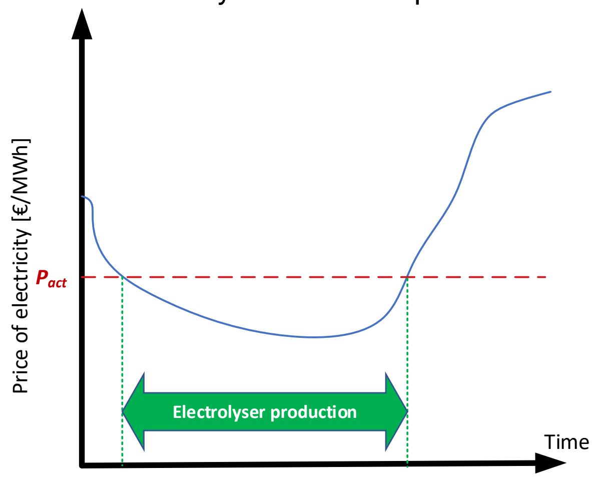


Figure 11: Activation price approach

The hydrogen prices are computed in accordance with Section 6.1 in Annex 1.

[9] The hydrogen price was assumed to be in the range of 14.67 – 17.84 €/GJ depending on the TY (see Annex 1, Section 6.1).
[10] Hydrogen production efficiency was adopted based on data provided by the TSO, ranging between 50 % and 85%, with a default of 68% (see Annex 1, Section 7.1).

8 CHP dispatch optimisation and heat credits

In some market zones, CHP units account for a large share of installed capacity. It is crucial to account for heat generation revenues when evaluating the economic viability of CHP units. These revenues directly contribute to the overall profitability of CHP units, which are often designed to meet both electricity and heat demands. Ignoring these revenues can lead to underestimating the unit's economic potential and might skew decisions regarding its operation or decommissioning. Additionally, CHP units operate with a unique must-run profile to ensure heat supply, which might result in power generation even when electricity prices are low. Without factoring in heat-related revenues, the assessment would overlook the added value that CHP units bring to the energy system by providing necessary heat, which can justify their continuous operation even during periods of low electricity demand. Therefore, including these revenues offers a more accurate picture of CHP units' economic viability, fostering better-informed decisions regarding their role in the energy mix.

The "heat credit method" was first introduced in the ERAA 2022 study, alongside the existing must-run approach,[11] to address the aforementioned problems: (i) the need to reflect the marginal cost of CHP units in the electricity price, and (ii) the necessity for some CHP units to be eligible for endogenous decommissioning. For the heat credit method, revenue profiles are provided for individual units in hourly granularity. These profiles are calculated based on an approach using PEMMDB data, measured historical time series of district heating demand, and standardised data from pre-processed Eurostat statistics (see Figure 12).

The "heat revenue tool" is shown in Figure 12. Using typical full load hours and the thermal capacity of each unit, slices of the overall heat demand time series are assigned to specific units. Combined with heat prices, each CHP unit receives a profile with revenues per MWh of electricity generated.

[11] Due to limited TSO or literature data availability for CHP units, the heat credit approach is only applied to public district heating CHP units. The must-run approach is applied to other types of heat networks, such as industrial heat networks, special district heating constructs, or heat generation from waste incineration.

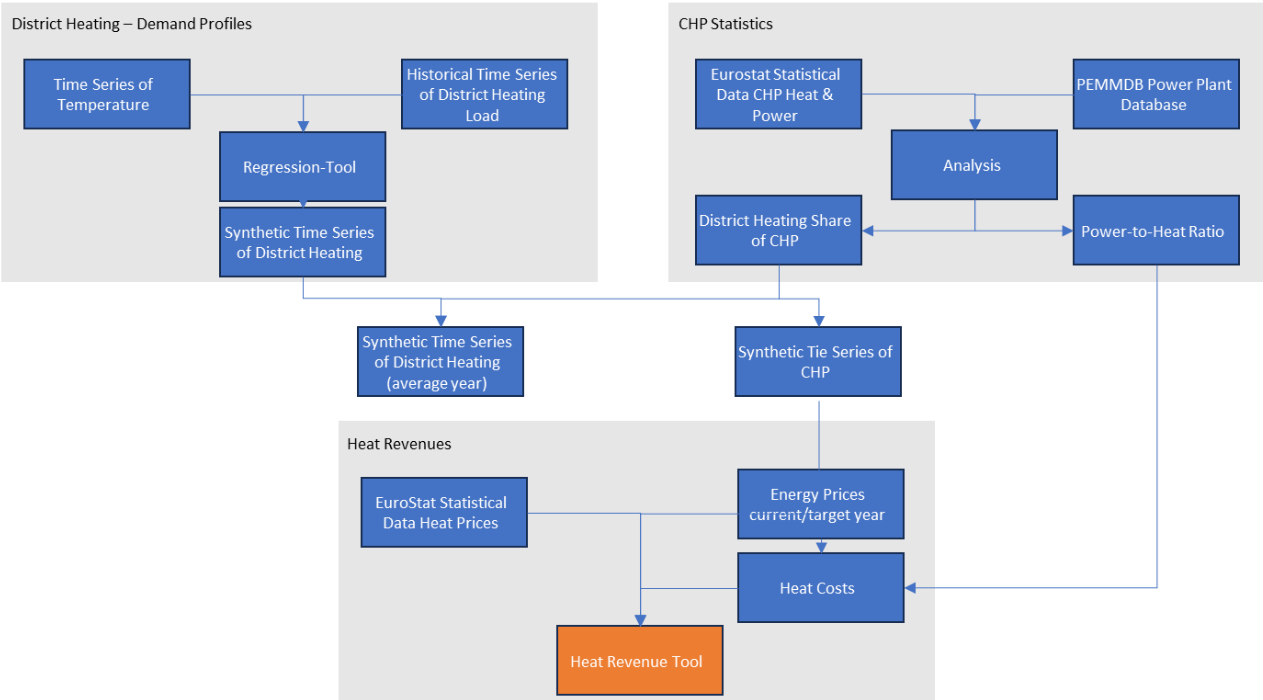


Figure 12: Heat revenue tool: input data and calculation methodology

Missing TSO data are complemented using Eurostat statistical data,[12] as shown in Figure 12. A mean heat demand profile is calculated and used with all WSs to minimise the amount of data processed.

Figure 13 shows the resulting stacked CHP unit dispatch (right graph) derived from the total district heating demand (left graph). The share of heat plants is not shown, as these units are not modelled in the ERAA.

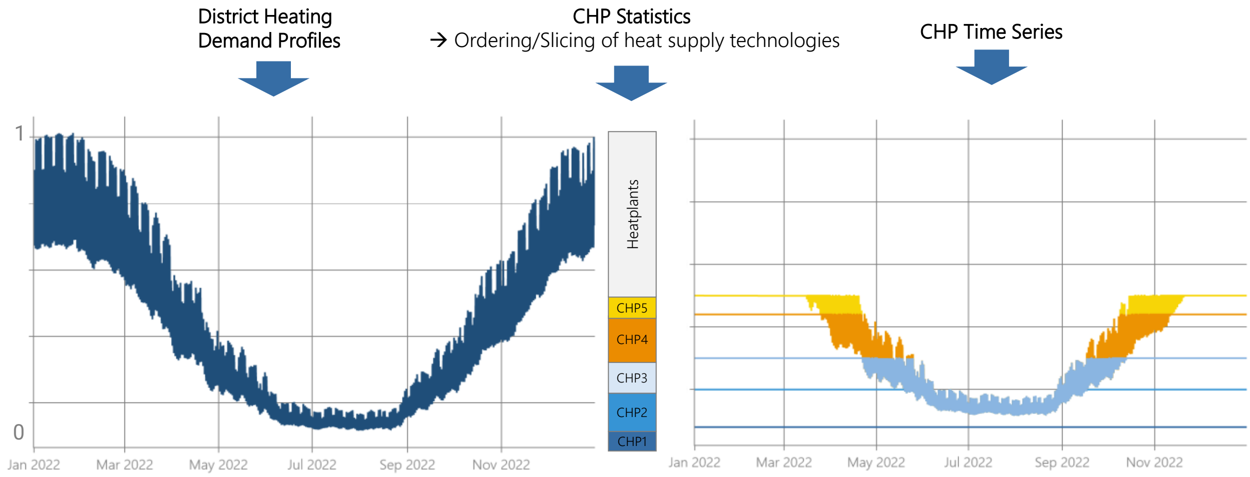


Figure 13: Illustration of splitting the heat demand between various CHP technologies

[12] Eurostat data browser: https://ec.europa.eu/eurostat/databrowser/product/view/nrg_bal_c?lang=en

The revenue profiles are derived from a thermal demand time series based on TSO-provided power-to-heat ratios and heat prices. Statistical data are used for any missing TSO values, with the exception of heat revenues, for which it is assumed that revenues correlate with the costs of heat supply provided by natural gas-fired heat plants. Therefore, heat revenues are dependent on the evolution of the gas price scenario.

In the total system cost optimisation, the heat credit method implies that CHP units have lower marginal costs at heat demand times. These units thus switch left in the merit order and their profitability is more advantageous due to additional revenues for heat supply than a similar unit (with the same technological configuration and fuel type) without heat extraction.

9 FCR and FRR balancing reserves

For each study zone, an amount equal to the total FCR and FRR capacity must be withheld from the EOM. From a modelling perspective, reserve requirements for balancing purposes can be accounted for by withholding generation capacity from the wholesale market or increasing hourly demand ("virtual consumption") and in both cases by the quantity of reserve requirements set by the Member States. The capacity withholding approach was adopted in ERAA 2025, as it has the advantage of not distorting the energy balance, and the resulting market prices as "virtual consumption" is not added.

Any reserve requirement quantities not directly withheld in the thermal generation capacities by the TSOs in the collected data are accounted for by procuring thermal capacities, reducing renewable production profiles, or reducing the maximum hydro, battery, or DSR capacities based on each TSO's suggestion.

If the TSO requests balancing reserve procurement from thermal, the respective capacity must be held back from the wholesale market. TSOs can withhold the thermal capacity of specific units for reserve requirements by reporting derated maximum unit generation capacities during the data collection. Another method is to specify the reserve requirement that should be covered by thermal units, after which the model identifies the cheapest possible method of providing the reserves from the units available to procure the balancing reserves. The decision is based on the calculated prices of capacity procurement as the dual values of the reserve requirement constraint. The available thermal units for providing balancing reserves have been assumed to be all thermal units within the given zone, except those with inelastic production profiles.

The reserve requirements for hydro units are modelled by capping the maximum hydro generation of either reservoir, open-loop pumped storage, closed-loop pumped storage units, or a combination, depending on the data reported by TSOs. The maximum generation value is calculated by subtracting the constant reserve capacity demand to be provided by the hydro unit from its turbine capacity.

The reserve requirements from renewable units are modelled by derating the maximum renewable generation of onshore wind, offshore wind, solar units, or a combination, depending on the data reported by TSOs. The maximum generation value is calculated by subtracting the constant reserve capacity demand to be provided by the renewable unit from its production profile, capping it at zero. This capping ensures no negative production profiles can occur in hours with low or no renewable production.

The reserve requirements for battery units are modelled by derating the maximum discharge capacity and energy storage capacity according to the data reported by the TSO. The maximum discharge capacity and energy storage capacity are calculated by subtracting the constant reserve capacity demand to be provided by the battery unit from its discharging and energy storage capacity.

The reserve requirements for explicit DSR units are modelled by derating the maximum activation capacity, i.e. the maximum reduction in load that the given DSR unit is capable of delivering, according to the data reported by the TSO. The most expensive DSR units are derated first to meet the reserve requirement. The maximum activation capacity value is calculated by subtracting the constant reserve capacity demand to be provided by the DSR unit from its activation capacity.

10 EVA methodology

The EVA step assesses the viability of capacity resources[13] participating in the EOM[14] using a long-term planning model to minimise total system costs.[15] The key decision variables of this long-term model aim to identify the economic-optimal (least-cost) evolution of resource capacity over the modelled horizon. Therefore, it delivers insights for each study zone over the TY, on the resource capacities that are likely to be (i) retired, (ii) invested in, (iii) (de-)mothballed, or (iv) extended in lifetime. The decision variables attributed to available resources depend on the specific technologies and fuel types of generation assets, in addition to country-specific data where applicable, e.g. thermal units eligible for (de-)mothballing or life extension (see Section 10.1 for more details about the EVA's scope).

Figure 14 indicates which inputs from the National Trends scenario are used for the EVA step. Since ERAA 2024, FB modelling has been introduced in the EVA to increase the consistency between the EVA and the adequacy models. Parts of the geographical scope where FB modelling has been introduced are modelled with simplified domains to cope with the computational complexity. This new input and assumed simplifications are further explained in Section 4.

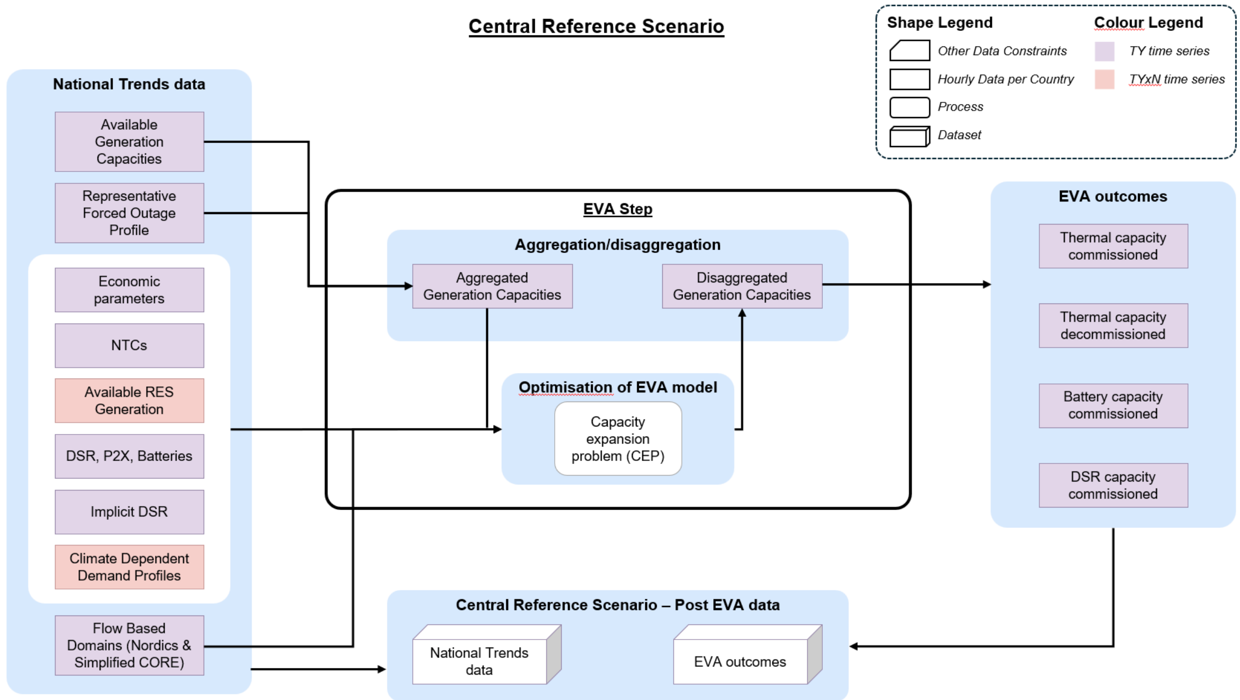


Figure 14: Overview of the inputs and outputs of the EVA step.

[13] Generation resources include storage units, e.g. batteries.
[14] Units with a capacity mechanism (CM) contract awarded are excluded from the EVA for the duration of their contracts.
[15] Article 6.2 of the ERAA methodology acknowledges the use of overall system cost minimisation for the EVA, albeit as a simplification and assuming perfect competition.

10.1 EVA technology scope

Only units that mainly depend on EOM revenues are included in the EVA scope.[16] In addition to decommissioning and new market entries, generation resources are eligible for lifetime extension[17] or mothballing/de-mothballing.[18] Table 11 summarises the decision variables of the EVA.

Table 11: EVA decision variables

Technologies	Decommissioning	Life Extension	Mothballing	New Entry
Natural Gas	✓	✓	✓	✓ (OCGT & CCGT)
Hydrogen				✓ (OCGT & CCGT)
Lignite/Hard Coal/Oil	✓	✓	✓	
DSR				✓
Battery (E/P = 6)				✓

Additionally, new entry decisions are limited by expansion constraints as elaborated in Sections 6.4.1 and 6.5 of Annex 1.

10.2 Capacity scoping

The EVA might use slightly different resource capacities as a starting point compared to the National Trends scenario, i.e. TSOs projections. The differences come from:

- Simplifying assumptions made on the decommissioning dates of the units subject to EVA. A unit subject to EVA is considered fully commissioned or not at all during a given year, whereby it cannot be commissioned or decommissioned at another moment than at the beginning of the year. The cut-off date is chosen as 1 July of any given year. A unit whose decommissioning date is before this date is not considered at all during the year of its decommissioning; otherwise, it is considered to be commissioned for the entire year of its decommissioning and effectively decommissioned the next year.

- Neglect of secondary fuels: for units with primary and secondary fuels, the primary fuel is assumed to apply to all of the unit's installed capacity.

[16] There might be additional exogenous assumptions for why units cannot be retired, such as local considerations, national policies, support schemes, and country specifications. Therefore, any other unit labelled by TSOs as a "policy unit" in the PEMMDB will not be a candidate for decommissioning. Similarly, must-run units or units with a CM contract in place are not considered as decommissioning candidates.
[17] Lifetime extension implies replacing or upgrading key elements of the asset to avoid a unit's retirement at the end of its initially calculated economic lifetime.
[18] (De-)mothballing is a common practice in the power sector that puts the unit in a temporary state of preservation with reduced fixed costs, and then returns it to service later when market conditions improve.

10.3 Non-consecutive target years

ERAA 2025 collected data for four non-consecutive TYs: 2028, 2030, 2033, and 2035. However, given that the EVA is an integrated model over multiple years for the 2028–2035 horizon, it is assumed that non-TYs are duplicates of the latest available TYs. For example, non-TY 2029 is assumed to have the same load, generation capacity, network constraints, etc., as TY 2028. To avoid unnecessarily enlarging the optimisation problem, this is implemented as a system cost weighting based on the number of intervening gap years.

The net present value (NPV) of capital expenditure (CAPEX) and fixed operations and maintenance costs (FOM) in the case of commissioned capacities is discounted uniformly over the represented years. For example, if OCGT capacity is commissioned in the first TY – which in fact represents the years 2028 and 2029 – the CAPEX and FOM are discounted, assuming a uniform increase of the capacity from 2028 until 2029, i.e. a half increase of the capacity in each year. This methodological decision is a compromise between assuming all fixed costs are already from 2028 onwards or only from 2029 onwards. This approach ensures a fair representation of financial parameters throughout the entire horizon.

10.4 Multiyear EVA optimisation function[19]

The EVA simulation is performed over multiple years. The total costs of the system in consecutive years are totalled in the EVA simulation by calculating the NPV of all future costs. A discount factor is applied to translate costs incurred in the future years to the present day value, as follows:

$$Minimize \quad \sum_{y} (1+r)^{(1-y)} [Total\ cost_y]$$

where: r – discount rate [%]

The total cost is equal to the sum of investment costs of new resource capacity (including a risk premium; see Section 10.12), fixed and variable unit operations and maintenance costs (including a risk premium; see Section 10.12), and DSR activation costs, in addition to the cost of curtailed energy represented by fictitious generators, with the marginal cost equal to the market price cap (see Section 10.9).

The resource capacity build cost represents the overnight cost of building a new unit, i.e. the all-in capital cost as per the commissioning date. Building a new resource means spending a "lumpy" capital cost with the expectation of benefiting from the favoured market conditions until at least the economic life of the resource. However, the economic life might exceed the modelled time horizon of the EVA, which is 10 years ahead. To resolve this, the build cost $CAPEX$ is converted to an equivalent annual charge, which is applied in the build year and every subsequent year.

$$Annuity = CAPEX \times \frac{WACC}{1 - \left(\frac{1}{1+WACC}\right)^{Lifetime}}$$

[19] The detailed formulation of the EVA optimisation model can be found in Appendix 1.

where: $WACC$ – Weighted average cost of capital
$Lifetime$ – Economic lifetime of the unit
$CAPEX$ – Capital expenditure

However, the finite 10-year time horizon for the use of annuity for new build units forces the model to build generators with low build costs even when their marginal generation costs are high. This is because the average generation cost between build years and the end of the planning horizon – including build costs – will be lower for such generators. To resolve this, we assume that the last year of the planning horizon is repeated an infinite number of times, while the annuity is considered in the objective function, but only for the economic lifetime of generation units. Table 12 shows the discount factor applied to each year of a 10-year planning horizon, assuming a discount rate of r%, and showing the perpetuity applied to the final year.

Table 12: Discount factor applied to each year of a 10-year planning horizon with perpetuity assumption in the final year

Year	Formula
1	$\frac{1}{(1+r)^{(1-1)}}$
2	$\frac{1}{(1+r)^{(2-1)}}$
3	$\frac{1}{(1+r)}^{(3-1)}$
4	$\frac{1}{(1+r)^{(4-1)}}$
5	$\frac{1}{(1+r)^{(5-1)}}$
6	$\frac{1}{(1+r)^{(6-1)}}$
7	$\frac{1}{(1+r)^{(7-1)}}$
8	$\frac{1}{(1+r)^{(8-1)}}$
9	$\frac{1}{(1+r)^{(9-1)}}$
10	$\frac{1}{(1+r)}^{(10-1)} + \frac{\frac{1}{(1+r)}^{(10-1)}}{r}$

In the above basic formulation, perpetuity – i.e. an implicitly infinite horizon – is assumed, despite the fact that the EVA model has a finite horizon. In this way, the objective function is expanded by the yearly costs – including the annualised build costs – after the final year of the horizon.

10.5 Weather scenario selection and reduction

Uncertainty is integrated into the multiyear model through the introduction of WSs, presenting three possible evolutions of climate and 12 weather conditions in each of these climatic evolutions, resulting in a total of 36 WSs.[20] Given a collection of WSs, the EVA model finds the optimal solution using a stochastic approach. This means that the optimal entry/exit decision of resource capacities – making up the $Fixed\ cost$ – is made by considering several possibilities of operational conditions, i.e. a set of WSs with their related weights ω_{WS} as follows:

$$Total\ cost_y = Fixed\ cost_y + \sum_{WS} \omega_{WS}\left[Operational\ cost_{y,WS}\right]$$

However, as formulated in Section 10.4, the EVA – especially when adopting the overall cost-stochastic modelling approach used in ERAA 2025 – is a complex and computationally demanding exercise. Therefore, it is necessary to reduce the number of WSs introduced. Due to this fact and to limit the number and duration of simulations, a direct approach is taken by solving the EVA model over a reduced number of WSs.

The reduction of the set of WSs is based on statistical properties. It was decided to reduce their number through an optimisation process aiming to minimise the differences in the distribution of net revenues from thermal technologies subject to EVA and DSR between the full set of WSs and the selected subset. The net revenues were taken from the ERAA 2024 post-EVA ED results. This analysis is performed ex ante to the EVA simulations, and selected WSs do not change during the protocol. Considering ERAA 2024 post-EVA ED results instead of ERAA 2025 pre-EVA ED results for the WS selection improves the expected representativeness and consistency with respect to ERAA 2025 post-EVA ED results. In addition, the selection of WSs is performed taking into account all TYs and FOSs to increase the representativeness and robustness of the approach.

For the selection of WSs, we extract and aggregate the yearly net revenues for the considered technologies per study zone. To account for the relative importance of each study zone in terms of its economic impact on Europe, the net revenues are expressed in absolute values. We then aim to minimise the Wasserstein distance between the net revenue distribution of the full set and the subsets of WSs for each study zone. For a single distribution, the Wasserstein distance can be understood as the difference between the empirical cumulative distribution functions (eCDFs). For a full set S and subset S_k, this distance can be understood as the area between the two curves:

$$W(S, S_k) = \int |eCDF(S) - eCDF(S_k)|$$

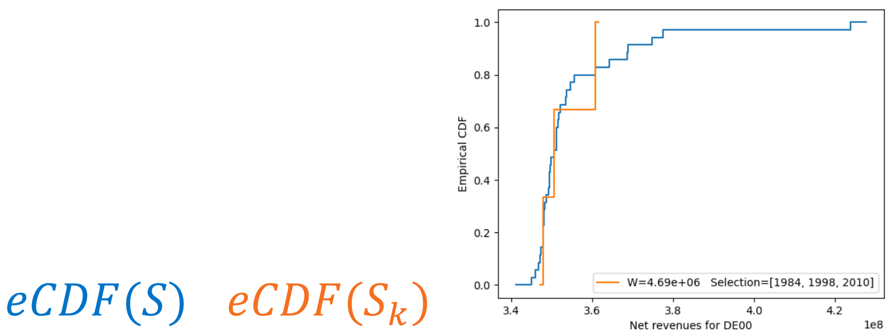


Figure 15: Selection of weather scenarios (Wasserstein graph)

[20] More details in Annex 1 – Section 3

The selection starts by selecting an array of candidates of subsets S_k. In ERAA 2025, the size of the candidate subsets is set at three to limit computation time and the problem size of the EVA model. All resulting candidates $\binom{36}{3} = 7{,}140$ can then be tested.

The best candidate subset is the one that minimises the total score as follows:

$$S^* = \min_{S_k} \sum_{BZ} W_{BZ}(S, S_k)$$

The present approach aims to find the most representative subset of WSs, with all of them weighted equally. Accordingly, equal weights are considered in ERAA 2025.

10.6 Unit aggregation

To reduce the size of the EVA model, generators are aggregated according to their main characteristics of node, technology, fuel and techno-economic parameters. This simplification is possible because (i) a uniform derating of NGCs in the EVA model based on FORs is considered instead of random draws of outage patterns, and (ii) the EVA model is solved in a linear manner.

As adequacy models use unit-by-unit data, it is necessary to post-process the aggregated EVA outcomes to increase granularity. For this purpose, a unit-based decommissioning approach is applied: within each aggregated EVA unit, the units are processed in a deterministic order (oldest commissioning date, then earliest decommissioning year, then alphabetical) and apply derating sequentially until the EVA capacity change is reached. Earlier units in the order may end up fully derated (effectively retired) and at most one “last” unit is partially derated to close any remaining gap. If a unit would be left with a capacity below 10 MW, it is fully retired.

The unit-based decommissioning approach achieves EVA’s block-level capacity targets with a transparent deterministic rule and produces more realistic inputs for adequacy: units are removed as whole assets where possible and at most one unit is partially derated. Compared with the ERAA 2024 uniform derating approach, this avoids spreading small residuals of capacity across many units, reduces ambiguity about which assets remain online, and yields outage/availability patterns that better reflect an actual fleet, while respecting EVA’s objective to determine overall viable capacity per technology in each study zone.

10.7 Maintenance profiles

The maintenance modelling of existing thermal units is simplified compared to the adequacy step by derating the available capacity of the units to reduce computational complexity. The derating of existing thermal units is based on the maintenance patterns calculated for the adequacy step as described in Section 5. The derating is applied to the aggregated units following the same logic as explained in Section 10.5.

For expansion and life extension candidates, a maintenance rate is applied as a derating factor of the generation capacity of some generation technologies. The derating factor is inversely proportional to the load profile in a given region to make more generation capacity available during times of higher load, and vice versa.

10.8 Modelling of forced outages

The methodology to compute FOs for generating units has been improved compared to previous ERAA cycles. Instead of simple arithmetic, an average representative outage pattern is applied in the EVA model. For this purpose, ED simulations are performed for each TY at the unit level before units are aggregated into the EVA, as shown in Figure 15. During this process, a representative outage pattern selection is performed. This allows the simulation tool to generate a mathematical model with multiple random FO profiles. Out of these profiles, the tool selects one that is most similar to others, making it a representative outage pattern. In this iteration of ERAA, a set of 15 outage samples was generated, which was then reduced to a single representative sample.

After the ED run, the availabilities of all units (non-profile-based thermal units that are set to have a FOR during the data collection) are converted into the corresponding EVA aggregated units, which essentially creates derating profiles based on a representative FO pattern. The result is a more realistic and accurate derating curve for the units compared to the simple arithmetic average used in previous ERAA publications. This method produces a plausible set of profiles that more accurately represent the FOs of power plants. Additionally, this approach ensures greater consistency between the ED and EVA ERAA modules.

As for NTCs, a derating equal to the line-specific FOR is applied in the EVA model to account for FOs. For borders where FB modelling applies, no additional FOs are taken into account since outages are already implicitly considered in FB domains.

10.9 Price cap evolution

The value of the price cap holds first-order importance when assessing the energy market viability of resource capacities. Price caps exist in markets mainly for technical reasons, in the interests of consumer protection, and to prevent potential anti-competitive practices. The current maximum clearing price of the DA market is 4,000 €/MWh. According to ACER's decision 2023/01,[21] in the event that the clearing price exceeds 70% of the harmonised maximum clearing price for single day-ahead coupling (SDAC) during at least two days within each rolling 30-day period, the latter shall be increased by 500 €/MWh the next day. However, if a transition period of 28 days is defined before the increase is applied for, this shall be applied in all relevant study zones 28 days later. During this period, no further price adjustments can be initiated.

The dynamic increase of market price caps described above cannot be modelled endogenously within the available market modelling tools used in ERAA 2025. Therefore, the yearly evolution of the DA price cap for all the TYs was estimated in a simplified manner, comprising the following steps:

(i) Building a set of WSs representing a 10-year horizon (i.e. 36 WS sets) using the available WS data, from WS 1 to WS 36 (for 10 years ahead) across 15 FO patterns (i.e. 36 × 15 = 540 multiyear scenarios).

[21] ACER Decision 01-2023 on HMMCP SDAC - Annex 1.pdf (entsoe.eu): https://www.acer.europa.eu/Individual%20Decisions/ACER%20Decision%2001-2023%20on%20HMMCP%20SDAC.pdf

(ii) Extracting hourly marginal prices for all MC samples for all TYs and study zones from the previous ERAA edition's post-EVA ED results.
(iii) Considering a starting price cap of 4000 €/MWh on 1 January 2024 and mimicking a dynamic price cap increase, applying ACER's rule based on the hourly marginal prices.
(iv) Computing a mean price cap value for each year of the study horizon.

Table 13: WSs representing a ten-year horizon

ERAA TY	YYYY	YYYY+1	YYYY+2	...	YYYY+10
15FO Scenario	WS 1	WS 1	WS 1	...	WS 1
	WS 2	WS 2	WS 2	...	WS 2
	...	...	...	...	...
	WS 36	WS 37	WS 38	...	WS 46
Price Cap (€/MWh)	PC	PC+Δ	PC+Δ	...	PC+Δ

These new price caps are then set as fixed input values for EVA and adequacy simulations.

Table 14: Ten-year scenarios considered for estimating the price cap evolution

Target Year	Price cap
2028	5,500
2030	6,500
2033	7,000
2035	7,500

10.10 Investor risk aversion

Following the ERAA methodology, the EVA shall aim to replicate the decision-making process followed by investors and market players. Investors generally show a certain level of risk aversion regarding their decision process. This means investors typically demand a risk premium on investments, i.e. investments that increase the risk of their portfolio should also increase the expected return of the portfolio. The volatility and uncertainty of the revenue projections, as well as the policy and scenario landscape that might affect the return on investment, are intrinsic conditions of investment risk in the electricity market. The ERAA approach relies on a theoretical and academic framework for investor behaviour,[22] merging concepts from utility and prospect theory. The rationale behind this approach is to overcome the limitations of a pure traditional capital asset pricing model (CAPM), which is not suitable alone considering the non-normal distribution of returns and downside risk stemming from the non-normality of the revenue (and price) distribution, in addition to the model and policy risk. All such elements cannot be properly captured using a pure WACC "base" model. The approach prescribes a transparent increase of the WACC (compliant with Article 6.9.iii.a of the ERAA methodology) using a "hurdle premium" specific to the technology and economic lifetime of the assets and within different scenarios (Figure 16).

[22] Source: https://www.elia.be/-/media/project/elia/elia-site/public-consultations/2020/20201030_200_report_professorboudt.pdf

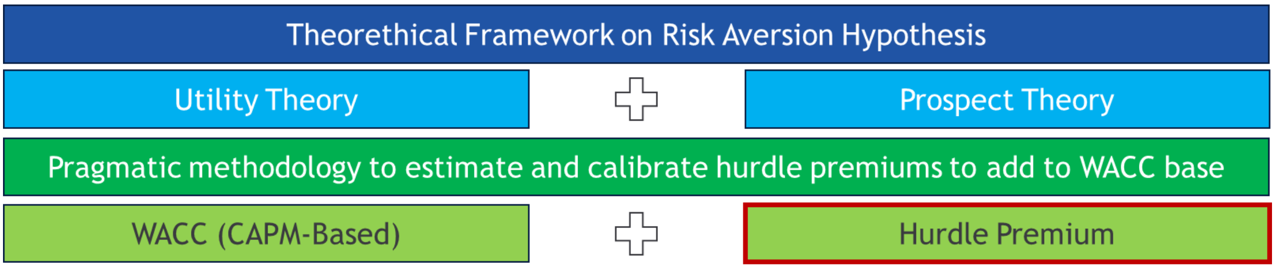


Figure 16: Theoretical framework on risk-aversion hypothesis

Hurdle premiums are set according to the deviation of actual returns from expected returns over a significant number of possible investment paths. The level and range of hurdled premiums primarily depend on two key drivers and how such risk drivers affect the specific technology:

1. The revenue distribution and the downside risk (under the simulation setup):
   - High price and revenue volatility in the distribution call for a higher hurdle premium
   - Intrinsically linked to the technology type and the merit order, e.g. higher for peak units compared to base load generators
2. Additional risks such as model risk and policy risk:
   - Difficult-to-capture real investor behaviour within the limited modelling framework and ruling assumptions.

These premiums are further calibrated, assessing the return impact of alternative scenarios considering standard $CAPEX$ and FOM costs but different levels of system adequacy, fuel prices, CO_2 prices, etc. While the hurdle premiums used have been calibrated on the Belgian electricity market,[23] such values can be extrapolated to other markets, if (i) the model and policy risk are applicable and consistent, and (ii) the distribution and downside risk are similar. Given that both conditions are valid in the ERAA modelling framework, such a calibration of hurdle premiums provides a robust yet pragmatic approach for considering risk aversion in the EVA.

The EVA in ERAA 2025 obtains a range of results by implementing two different risk-aversion modelling approaches: (i) with the enhanced hurdle premium only, and (ii) with the enhanced hurdle premium combined with a revenue cap to reflect improved and risk-profile-aligned investor risk-aversion modelling, based on the observed revenue distribution and expansion decision characteristics:

- The enhanced hurdle premium only approach includes an update of hurdle premiums for OCGT and CCGT expansion candidates, based on the results of ERAA 2024, while the remaining hurdle premiums remained the same. This update applies a constant absolute risk aversion (CARA) utility function to better reflect investor preferences under uncertainty, particularly for technologies with high exposure to price volatility. Hurdle premiums for other technologies remain unchanged. (See the "010.10.1 Hurdle " section.)
- The enhanced hurdle premium combined with a revenue cap approach builds on the enhanced hurdle premium and additionally introduces a value-at-risk (VaR) related

[23] Source: Boudt K., 2022, Analysis of hurdle rates for Belgian electricity capacity adequacy and flexibility analysis over the period 2024-2034

approach to cap maximum expected revenues per hour. This is achieved by reducing the maximum hourly electricity price considered in the EVA, thereby limiting the influence of extreme price spikes on investment viability. This adjustment ensures that revenue projections better reflect realistic monetisation potential under adverse conditions and complements the hurdle premium approach. (See the "10.10.2 Revenue " section.)

The implementation in the EVA works by leveraging specific "hurdle rates" per technology (and country where applicable), defined as:

$$HurdleRate = WACC + HurdlePremium$$

The hurdle rate is then used to calculate the annuity of $CAPEX$, as follows:

$$Annuity = CAPEX \times \frac{HurdleRate}{1 - \left(\frac{1}{1 + HurdleRate}\right)^{Lifetime}}$$

The hurdle rate also adjusts the FOM of existing units. As the FOM (noted FOM^* in the equation) is a yearly cost, the annuity of FOM (noted FOM in Appendix 1) is calculated assuming a one-year lifetime.

$$FOM^* = FOM \times (1 + HurdleRate))$$

To summarise, under this framework, investing in new (or existing) capacity is economically viable when the expected return exceeds the hurdle rate assigned to such capacity, which is set equal to the cost of capital of a reference investor plus a hurdle premium. The latter serves as a cushion to compensate for the deviation of the "asset cost of capital" from the reference investor's cost of capital based on the predicted project risk under the base scenario, and the model and policy risk related to the scenario ED outcomes within the probabilistic MC assessment (e.g. non-normal revenue distribution and model risk), and uncertainty about the evolution of the scenario landscape assumptions over the different TYs considered (e.g. policy risk).

ERAA results strongly depend on the assumptions that define the central scenario (e.g. commodity prices, cost of new entry (CONE) values, WSs, policy targets). Beyond the projected revenue distributions obtained from the simulations, investors would likely also consider alternative scenarios. These uncertainties can be only partially covered by the hurdle premium calibration, which is based on a predefined combination of quantitative and qualitative conclusions.

As an example, investors' expected returns are likely to combine the outcomes of both adverse and favourable scenarios. The risk profile or "appetite" of each investor determines the "weight" they attribute to adverse scenarios compared to the base or favourable scenarios. The more negative the effect of a plausible adverse scenario, the higher the hurdle rate.[21]

Since the expected return calculation used in the EVA of the ERAA is limited to the boundaries of using a single reference scenario, we shall reflect on the uncertainties that may or may not be captured through the hurdle premium calibration.

Last year's findings showed, that the distribution of revenues across the applied projected WSs revealed a particularly challenging risk profile. This highlighted the importance of incorporating revenue distribution information into the risk-aversion modelling, making the update a highly relevant and timely improvement.

Therefore, a periodical review and updates of the hurdle rates considered are recommended, and are conducted for the first time in ERAA 2025 through the update of hurdle premiums for OCGT and CCGT technologies based on results from ERAA 2024.

Nevertheless, it becomes apparent that not all plausible risks relevant for investor decisions can be fully captured via the hurdle premium approach and its calibration. Therefore, additional complementary risk-aversion approaches – such as those presented in the ERAA methodology and reflected in the scenario-enhanced hurdle premium combined with a revenue cap – shall be investigated in parallel.

10.10.1 Hurdle rate update

In ERAA 2025, the hurdle premiums for newly built conventional generation technologies, specifically OCGT and CCGT, have been updated, improved, and aligned with the observed risk profile of expansion decisions. This update is based on findings from ERAA 2024 and represents the first application of a CARA utility function in the calibration of hurdle premiums.

The profitability of OCGT and CCGT units is highly dependent on scarcity pricing, which introduces significant volatility and downside risk in their revenue distributions. Analysis of ERAA 2024 results revealed that the distribution of revenues across the applied WSs showed a challenging and asymmetric risk profile, particularly for peaking units. This justified a revision of the hurdle premiums to better reflect investor risk aversion under such conditions.

In contrast, battery storage technologies exhibit a day/night operation profile and are less exposed to scarcity pricing. Moreover, the number of battery expansion candidates in ERAA 2024 was limited. As a result, the risk premium for batteries remains low, and no changes to the existing hurdle premiums are proposed for this technology.

Similarly, existing units and DSR remain open topics for future methodological development. Given the already high level of decommissioning of existing units in ERAA 2024 and the limited expansion potential for DSR, no changes to their hurdle premiums are proposed at this stage.

The hurdle premium update was carried out using the following steps:

Based on academic literature, the CARA utility function is commonly used to model investor behaviour under uncertainty. The CARA utility function is defined as:

$$U(x) = -e^{-\alpha x}$$

where:

- U(x) is the utility of monetary outcome
- α is the coefficient of absolute risk aversion.

The certainty equivalent (CE) represents the guaranteed monetary amount that yields the same utility as the expected utility of an uncertain outcome. For a given expected utility $\mathbb{E}[U(x)]$, the CE is calculated by inverting the utility function:

$$CE = -\frac{1}{\alpha}\ln\left(-\mathbb{E}[U(x)]\right)$$

This means that after computing the expected utility of the uncertain cash flows using the CARA function, the CE is derived by applying the inverse transformation. The difference between the expected monetary value and the CE reflects the risk premium required by the investor.

An alpha value > 0 models risk-averse investor behaviour. The alpha value of 0.0075 reflects a moderate level of risk aversion,[24] assumed as appropriate for modelling investors in the electricity market. It implies that investors are sensitive to downside risk and require a premium to compensate for uncertain or volatile returns, especially for technologies like OCGT and CCGT that are exposed to scarcity pricing.

The new hurdle premiums are derived by calculating WS-specific profits for all expansion decisions made in ERAA 2024. Profits or losses are then converted into CEs using the defined utility function parameters. The difference between the expected revenue and the CE represents the risk premium, which is subsequently translated into an updated hurdle premium. Finally, the individual hurdle premiums for each expansion decision are aggregated using a capacity-weighted average, leading to the following values:

Table 15: Updated hurdle premiums for OCGT and CCGT[25]

	ERAA 2024	ERAA 2025
OCGT	6.0%	9.9%
CCGT	4.5%	6.9%

It is evident that investments in CCGT tend to exhibit a lower risk profile, partly due to fewer extreme fluctuations and the occurrence of individual years with exceptionally high revenues. Figures 2–4 in Annex 3 of ERAA 2024 clearly demonstrate this, showing significantly higher capacity factors for CCGT compared to OCGT, along with a slightly lower sensitivity of CCGT revenues to weather-year-driven scarcity situations.

It is acknowledged that the approach chosen for updating the hurdle premiums represents only a first step toward modelling risk aversion. Given the various uncertainties associated with applying this methodology, a conservative approach was deliberately adopted. This approach will need to be continuously refined in future iterations of the ERAA. In line with a pragmatic methodology, the initial focus was placed solely on updating the hurdle premiums for candidate technologies. These investments carry the highest degree of uncertainty, as indicated by the results of previous ERAA versions, which showed extremely uneven revenue distributions across the considered weather years (see also Figure 15).

[24] Source: Risk and Probability Premiums for CARA Utility Functions on JSTOR
[25] Annex 1 includes a complete list of hurdle premiums.

10.10.2 Revenue cap

A survey conducted by ENTSO-E among European energy market actors in March 2025[26] **showed that investors' decisions on decommissioning existing capacity and building new units do not rely on very high price spikes that occur only a few hours per year. The appearance of these prices is highly uncertain, and without them, the activity would be economically unsustainable. Therefore, a cap has been applied to the revenues that market actors can receive in the EVA analysis in order to mitigate the influence of price spikes on the results.**

The revenue cap for the first TY (2028) was identified by studying historical data and conducting market simulations on forecast scenarios. The 99th percentile was adopted to ensure the inclusion of the vast majority of price occurrences. In this way, the value 1,000 €/MWh was reached. The price cap for the following TYs has been computed starting from this value and applying the same rate at which the price cap addressed in Section 10.10 increases. Table 16 reports the revenue caps applied to each TY.

Table 16: Revenue cap

Target Year	Revenue cap [€/MWh]
2028	1000
2030	1200
2033	1300
2035	1400

10.11 Centralised approach for estimating explicit DSR potential

As introduced in Annex 1, Section 6.5, a stepwise approach is used to determine the additional explicit DSR potential beyond the National Trends assumptions depending on available country data. If no DSR potential is available from a published official VoLL/CONE study or national study for DSR reported by the TSO, ENTSO-E uses a centralised bottom-up approach to determine any additional explicit DSR potential. Figure 17 illustrates the approach used.

[26] The results of this survey were published by ENTSO-E and can be found at the following link: https://eepublicdownloads.blob.core.windows.net/public-cdn-container/clean-documents/sdc-documents/ERAA/ERAAMethodology_InvestorSurvey_Results_Publication.pdf

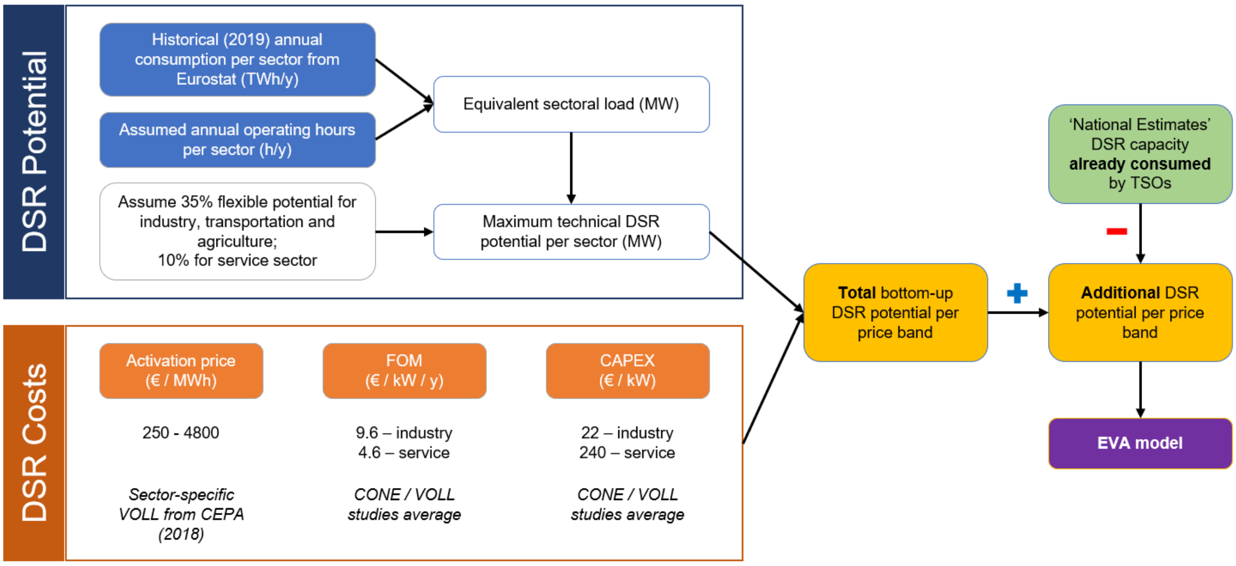


Figure 17: Overview of the explicit DSR potential estimation methodology

The maximum technical DSR potential (per industrial sector[27] per country) is estimated based on:

- annual sector electricity consumption from 2023 from Eurostat;
- assumed 8,760 operating hours per year (i.e. baseload);
- assumption on the flexible industrial, transportation and agriculture load (35%)[28];
- assumption on the flexible service sector load (10%); and
- no minimum threshold on the capacity of DSR from a given industry sector is applied to avoid the risk that the approach overlooks additional DSR capacity in smaller countries.

The potentials are combined with assumed cost parameters, based on the following sources:

- sector-specific VoLL values from CEPA (2018) as a proxy for the activation price[29];
- FOM value derived from the available VoLL/CONE studies, whereby an average is made per sector across the VoLL/CONE studies where DSR is a reference technology and used as a single value for DSR potential; and
- CAPEX value, following the same approach as for the FOM.

To prevent the double-counting of DSR capacity, the DSR capacity accounted for in the 'National Trends' scenario is subtracted from the maximum technical DSR potential for each country.

This simplified bottom-up approach is necessary given the lack of high-quality, consistent EU-wide datasets for DSR. However, due to the stepwise approach applied this year, this fallback is applied to a few countries across Europe. Thirty-two study zones have DSR potential, including nine with national studies or TSO-estimated DSR potential and six with a VoLL/CONE study. As more

[27] Residential DSR is not considered in the centralised approach.

[28] Due to limited data on the flexible share in the literature, this assumption was set in ERAA 2023 by adjusting the flexible share until the total DSR potentials approximately matched the estimated potentials from available national studies. As a sanity check of this 35% assumption, the calculated total DSR potential per country as a share of peak demand fell in the range of 10% – 20%, comparable with other studies.

[29] CEPA (2018) study on the estimation of the value of lost load of electricity supply in Europe

VoLL/CONE and national DSR studies become available, ENTSO-E will endeavour to use these in future years for the ERAA and to improve the modelling of DSR.

10.12 Revenue consistency of the EVA model with the Adequacy model

Consistency checks were conducted throughout the study between the investment module (EVA) and the main adequacy model (i.e. ED model). Revenues from technologies which are subject to the EVA were used as a key cross-model metric.

Figure 18 reports average revenues calculated on the full 36 WS set for the post-EVA ED model and on the set of 3 selected WSs for the EVA. The differences observed are mainly driven by the representation of FO patterns (1 representative sample for the EVA and 15 different samples for the ED) and the use of the 3 out of 36 WS subset, which naturally affect the realised marginal prices and thus the revenues captured by the EVA model (thereby driving decisions on market capacity), compared to the revenues extracted ex-post from the ED models. The comparison suggests that deviations arise from current modelling limitations in scope and scenario coverage, due to the necessary simplifications to manage runtime and complexity, rather than structural inconsistencies in the investment signals between the EVA and the ED models. An analysis and benchmark of the representativity of the selected subset of 3 WSs used in the EVA model is presented in Annex 1. The high differences in magnitude for some specific areas are exacerbated by the high values of the price caps (up to 7500 €/MWh in 2035), which can cause very high differences in "potential" theoretical revenues even in case of a relatively modest number of different hours for which a price spike may be observed.

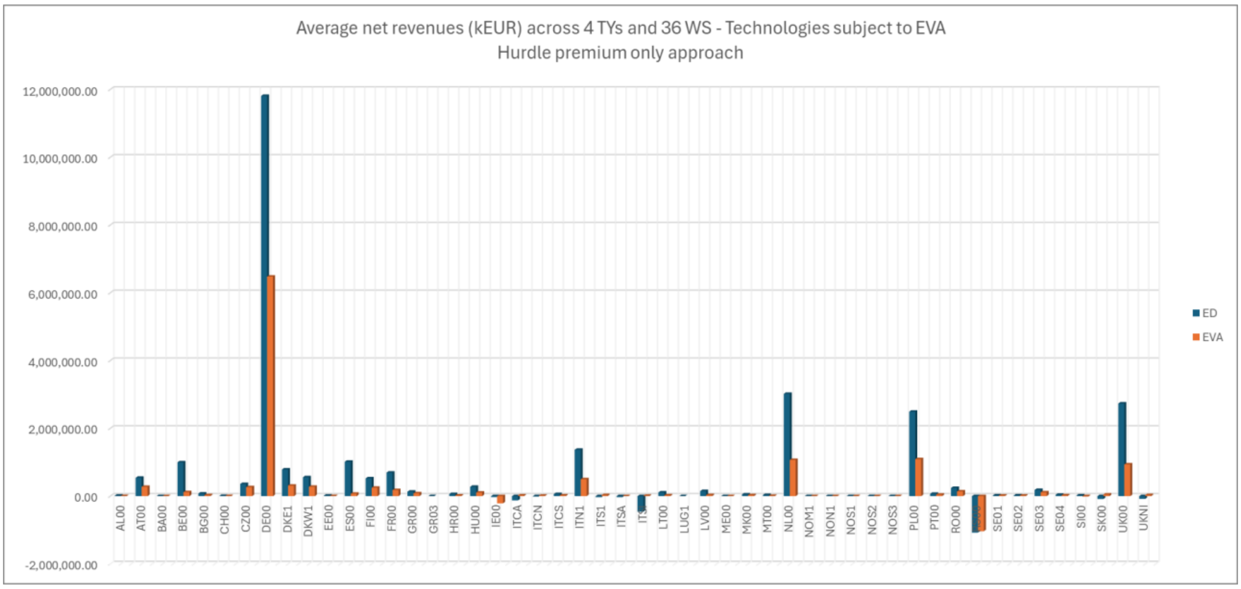


Figure 18: Average net revenues (kEUR) per study zone – ERAA2025 hurdle premium-only approach

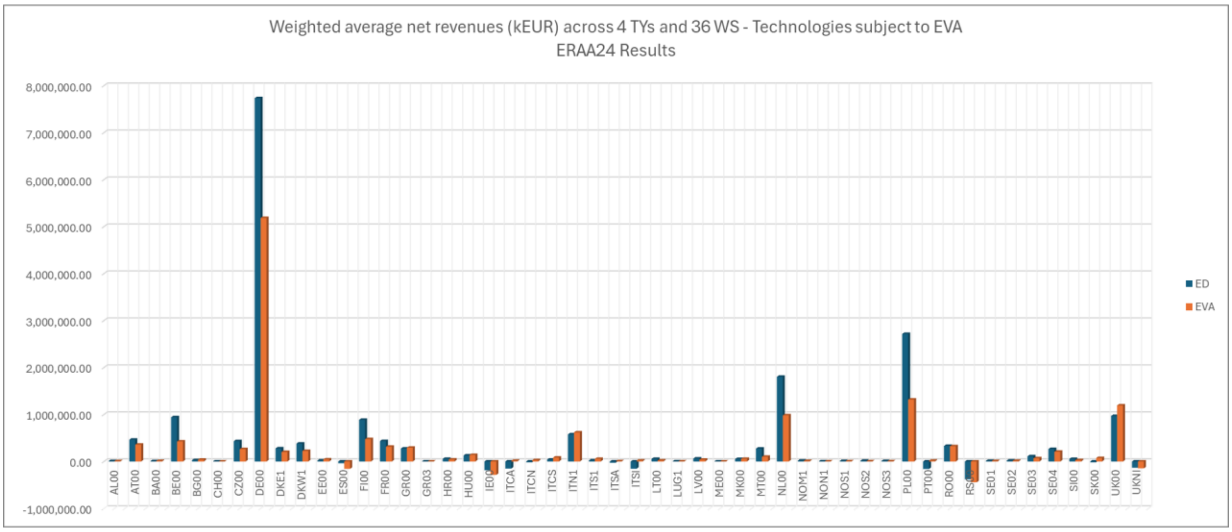


Figure 19: Weighted average net revenues (kEUR) per study zone – ERAA 2024 results

Figure 19 presents the same comparison based on ERAA 2024 results, where the 3 WSs used for EVA differ from the ones used in ERAA 2025 and which were considered with specific weights within the EVA model, as explained in the ERAA 2024 report. Despite ENTSO-E efforts to constantly improve the quality and the robustness of ERAA results, no substantial improvements could be achieved in ERAA 2025 compared to the previous ERAA edition, in terms of "absolute" consistency between the EVA and the ED model. This is confirmed by Figure 20, which reports the relative ED and EVA difference in revenues for significant bidding zones, taking the ED revenues as reference. For readability, extreme outliers were excluded.

This confirms that the limitations imposed by the current EVA setup, i.e. stochastic overall-cost minimization approach including only 3 out of 36 WSs and 1 out of 15 FO sample, does not allow to achieve substantial improvements in strict consistency terms and that the final level of consistency achieved is not predictable at the beginning of the process, despite the good representativity of the selected WSs. Improvements are expected with the deployment of the revenue-based approach, e.g. by allowing the inclusion of more WSs as show-cased in Annex 5. However, ENTSO-E would like to underline that "consistency" in EVA should not be targeted in terms of mere "equality" in revenues or other KPIs with respect to the ED module, but it should be addressed considering and understanding the different scopes of the two models. Notwithstanding the necessity of consistency in modelling and assumptions, the objective of the ED is a state-of-the art identification and quantification of the resource adequacy risks, while the EVA aims at an appropriate and robust consideration of best practices of investor behaviour and decision-making in the energy sector. These two different objectives typically do not coincide.

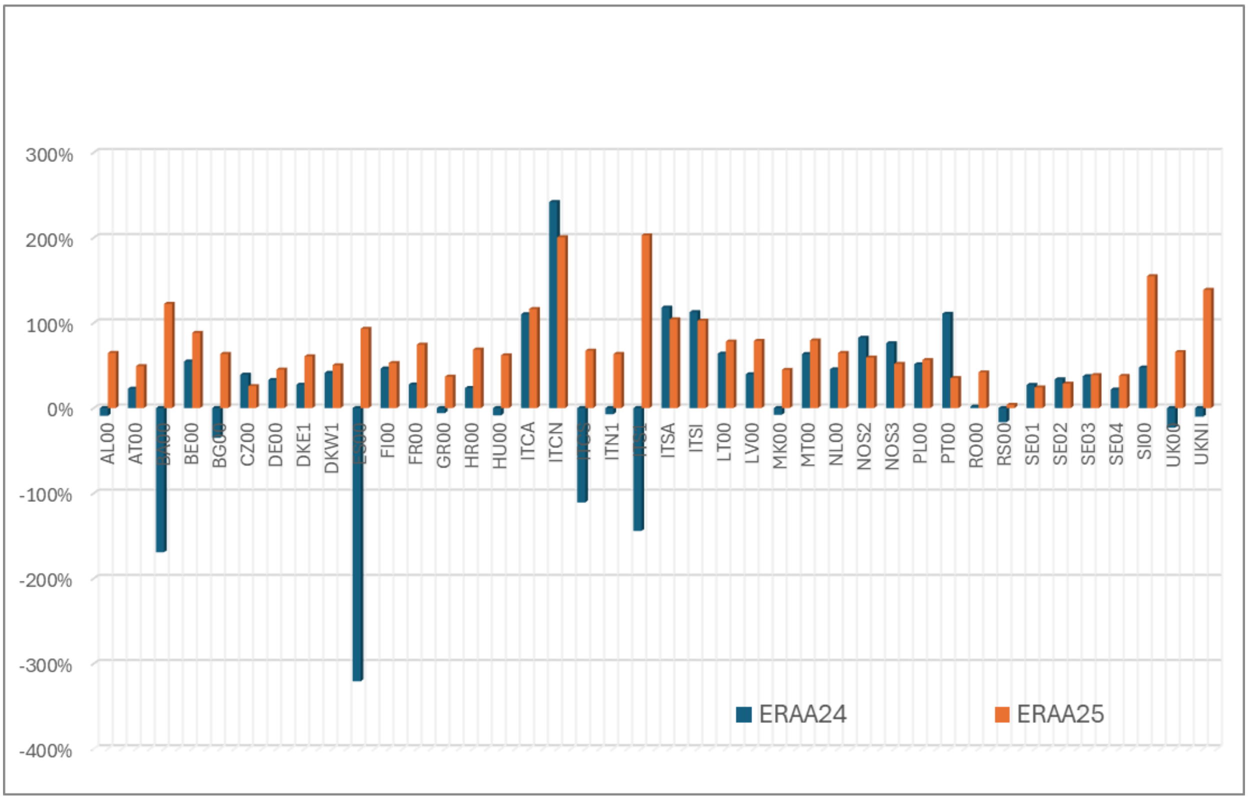


Figure 20: Relative revenue difference between adequacy and EVA revenues per study zone

11 Adequacy assessment methodology

The objective of the ERAA adequacy study is to calculate the risk of security of supply of the post-EVA scenarios by calculating loss of load expectation (LOLE) and expected energy not served (EENS) metrics (see Section 11.2 for the mathematical expression). A modern adequacy assessment accounts for uncertain variables in the system and offers a probabilistic indicator of the adequacy situation under several plausible realisations of the uncertain system variables. The state-of-the-art methodology in adequacy studies is the MC simulation approach. To avoid any confusion, the MC approach is not applied in the EVA step.

11.1 Monte Carlo adequacy assessment

The MC simulation comprises a large number of scenarios, featuring different asset FO realisations/draws for each given TY and WS. More specifically, these FOs occur for the thermal generation and transmission assets (HVDC and HVAC interconnections), and their impact on the installed capacities is known during the UCED step (see Section 11.5). The combination of random outages and climate scenarios results in a large set of possible system states to be modelled for each TY. The results can then be assessed probabilistically, which is well-suited for modern volatile power systems. The detailed process is described below.

The process starts by defining the climate scenarios, representing projected WSs covering the whole time horizon. Each WS represents a consistent set of:

- temperature-dependent demand time series;
- wind and solar load factor time series;
- time series for hydro generation, inflows, minimum/maximum generation or pumping capacity, and minimum/maximum reservoir level (where applicable); and
- climate-dependent time series for other RES and other non-RES generation.

As a second step, multiple sets of random FO realisations (hourly time series) are generated for each WS (*M* FOSs per WS, where the quantity *M* is only known after model convergence is reached). FO realisations do not affect the planned maintenance schedules (more details on the convergence can be found in Section 11.6).

Each model run is executed for one WS and one random FO realisation, referred to as an MC year. The combination of *N* WSs and *M* FO realisations per WS results in a total of $N \times M$ model runs. Each model run is optimised individually. Figure 21 illustrates the MC approach described for each TY studied.

For more information on input data, please refer to Annex 1.

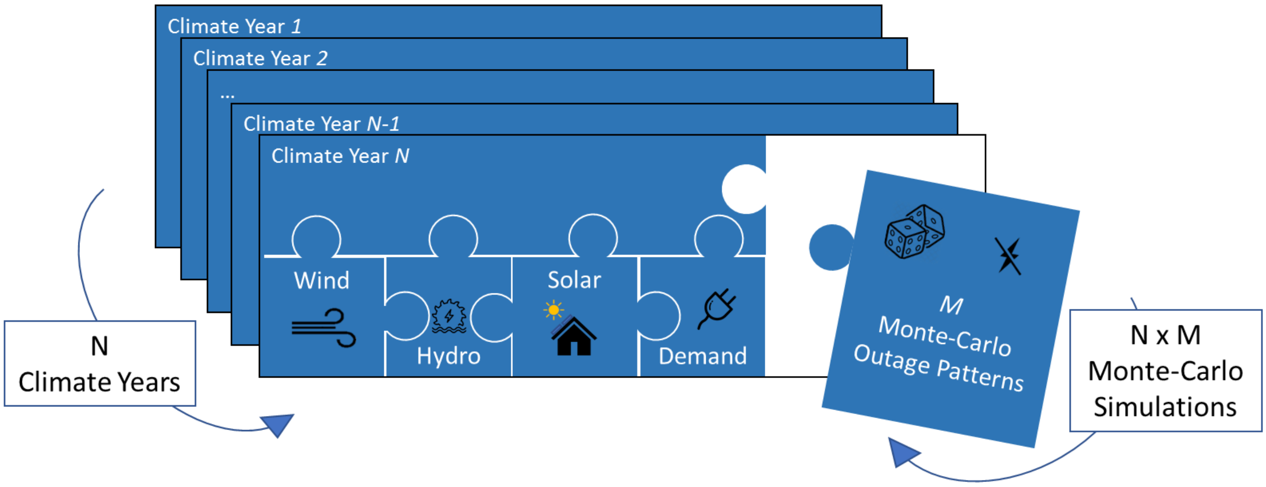


Figure 21: Monte Carlo simulation principles for a given target year

11.2 Adequacy indicators

In probabilistic adequacy studies, the typical indicators for resource adequacy are either the expectation of indicators (e.g. the EENS) or a percentile of the independent indicator values (e.g. 95th percentile of the ENS values). The following indices are used to assess the adequacy levels for a given geographical scope and a given time horizon:

- **Loss of load duration (LLD) [h]:** The duration in which resources (e.g. available generation, imports, demand flexibilities) are insufficient to meet demand. This does not indicate the severity of the deficiency (ENS). Note that the model has an hourly time resolution, which therefore also transfers to the granularity of the LLD indicator.
- **LOLE [h]:** The expected number of hours during which resources are insufficient to meet demand over multiple scenario runs, i.e. WSs and/or FO realisations. LOLE can be calculated as the mathematical average of the respective LLD over the considered model runs, according to Eq. (1), in which J is the total number of considered model runs and LLD_j is the LLD of model run j:

$$LOLE = \frac{1}{J}\sum_{j=1}^{J} LLD_j \qquad (1)$$

- **ENS [GWh]:** The sum of the electricity demand that cannot be supplied due to insufficient resources. For a geographical scope with multiple nodes, ENS refers to the total ENS of all its nodes. A null ENS suggests that there are no adequacy concerns.
- **EENS [GWh]:** The electricity demand that is expected not to be supplied due to insufficient resources. For a geographical scope with multiple nodes, EENS refers to the total EENS of all its nodes. EENS can be calculated as the mathematical average of the respective ENS over the considered model runs, according to Eq. (2), n which J is the total number of considered model runs, and ENS_j is the ENS of model run j:

$$EENS = \frac{1}{J}\sum_{j=1}^{J} ENS_j \qquad (2)$$

Note that the final adequacy indicators in ERAA 2025 reflect the impact of the curtailment sharing (CS) implementation in the adequacy assessment, as described in Section 11.7.

11.3 Maintenance for market entries

As described in Sections 5 and 10.7, maintenance profiles for thermal unit references in the central reference scenario data are the output of an optimisation step. For units entering the market as a result of the EVA step in the respective TY (de-mothballed, life extended, or new build units), no planned maintenance is considered, as it is assumed that it will occur during times of oversupply and thus not significantly affect reliability standards. Nevertheless, these units are subject to FOs, as described in Section 11.4.

11.4 Forced outage profiles

The following parameters are provided by TSOs to describe outage behaviour:

- FOR, i.e. the likelihood of a FO;
- Mean time to repair, i.e. the duration of a FO
  (default: line – 7 days; nuclear unit – 7 days; gas & coal unit – 1 day).

FORs are fundamental parameters for computing FO profiles. They represent the probability of a power plant or an interconnection being out of service unexpectedly for a period of time. These parameters must be set up carefully, considering the amount of capacity (thermal generation and interconnection capacity) they can put out of service. FORs are expressed as a single percentage for each generation unit or interconnector and provided for individual TYs, reflecting power plant or interconnection upgrades or renewals.

FORs are applied on a unit-by-unit granularity for thermal units and depend on the technology and characteristics. In the absence of FORs provided by TSOs, a default representative value based on the given technology is used. A similar mechanism is applied to interconnections: for some interconnections, input data already explicitly consider outages, while in other cases, random outages on interconnectors are drawn per pole based on FORs (i.e. at borders with multiple poles, an outage of one pole does not reduce the NTC to zero).

FO profiles are generated randomly within each modelling tool for each stochastic element in the simulation, namely resource units and interconnection lines. Based on the parameters mentioned above, FO profiles are drawn describing the hourly availability of each stochastic element of the system. They can have a significant impact on resource adequacy due to their uncertain nature. Therefore, it is important to draw a sufficient number of possible outage realisations to assess the impact on adequacy in expectation.

11.5 Unit commitment and economic dispatch

The unit commitment problem aims to identify the optimal combination of on/off decisions for all generating units across a given horizon. The on/off decisions must imply both a feasible solution and an optimal solution regarding the total system cost, including the cost of start-up and shutdown. The ED refers to optimising generator dispatch levels for the given unit commitment solution. The UC and ED are co-optimised to minimise the combined costs.

More specifically, the UCED optimisation is a two-step approach with a system cost minimisation target, i.e. it strives to minimise the sum of electricity production costs (being the main components of the costs: the fuel price, emission price and VOM) under the constraint that electricity consumption must be fulfilled. In the first step, an annual optimisation for the TY is undertaken to account for intertemporal energy constraints that might span the whole year. Multiple hours are aggregated and optimised in blocks to deal with the large optimisation problem in a reasonable computation time. The energy limits constraint includes optimising available hydro resources, as described in Section 6.1. The optimised maintenance schedule for thermal units computed as described in Section 10.7, is anticipated and considered by the pre-optimisation.

The outcome of the hydro optimisation step comprises more granular daily target values for objects with annual constraints. In the case of hydro units, this results in daily reservoir targets that are set as soft boundaries to the total hydro energy available over the day for the subsequent, more granular optimisation step.

The UCED optimisation is then performed in smaller/finer time steps (e.g. one day) to determine which units are dispatched for each hour of the optimisation horizon (TY) in addition to the respective dispatch level for each unit. For the optimisation, a given TY is divided into several UCED optimisation time steps/horizons. For each resulting UCED, the problem is optimised based on the hourly system state (demand, RES feed-in, available thermal generation, NTC/FB constraints). Subsequently, each UCED problem is given the final system state of the preceding UCED problem (used as the initial dispatching state for the current UCED problem). Indeed, optimising a given UCED problem with a different initial dispatching state while keeping other parameters unchanged might yield different results, as would, dividing a TY into a different set of UCED problems. The entire UCED optimisation process is visualised in Figure 22.

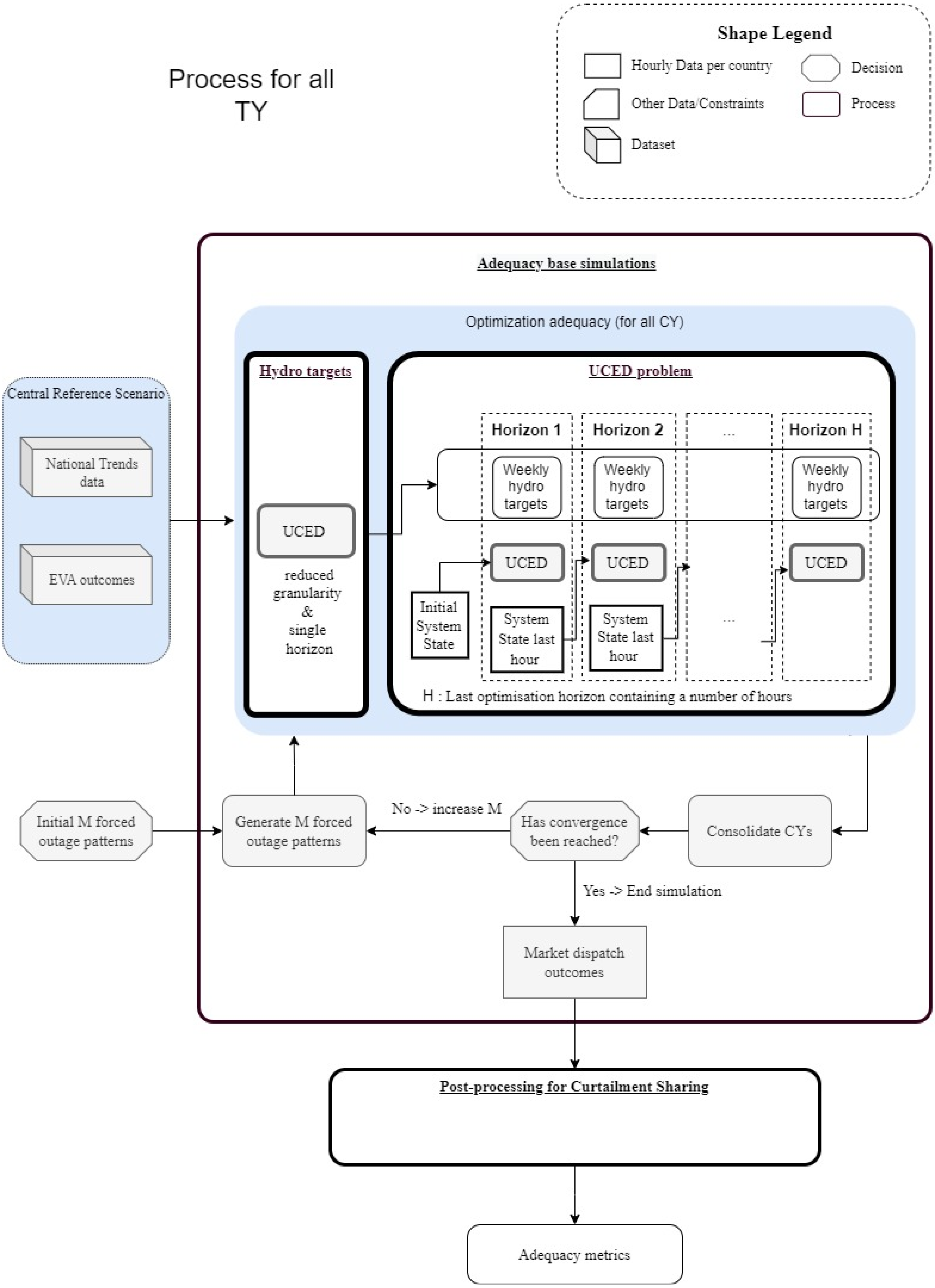


Figure 22: UCED problem

The UCED optimisation problem solver employs flexible hydro storage resources such as reservoirs and PSPs to exploit marginal price gain opportunities from a cost minimisation perspective. The exogenously provided generation constraints and reservoir level trajectories are accounted for by the solver. Final marginal prices are a direct result of the hourly optimisation of hydro storage and are set equal to the highest marginal cost (merit order) of the dispatched resources (e.g. RES, thermal, DSR, imports, etc.) to cover the hourly domestic demand. As such, the residual load[30] is matched with the least-cost available resource capacities and hydro resources, and is sometimes referred to as "hydro-thermal" optimisation. It follows intuitively that storage injection occurs in times of low capacity margins (high electricity prices), whereas storage off-take occurs in times with high capacity margins.

In a system with a high degree of flexibility (i.e. implicit DSR technologies, battery storage systems, hydro storage), the storage dispatch in scarcity periods can affect adequacy indicators.[31] It is therefore necessary to properly account for storage operation strategies in scarcity periods, in particular to avoid an arbitrary temporal distribution of ENS. In this study, a modelling approach minimising the peak residual load has been applied. It is an integral element of this methodology that the total ENS volume and thus the system costs are not increased by the homogenised temporal ENS distribution.

11.6 Monte Carlo convergence

FO realisations might affect model results depending on the specific demand and supply situation assumed in the given MC year. For example, a major power plant experiencing a FO might lead to severe adequacy risk in a high-demand and low-renewable-energy-production situation, whereas it might have a negligible impact in a high-renewable-energy-production situation. Therefore, model run results might significantly differ. Figure 23 illustrates this aspect, showing a schematic histogram of the ENS over 525 MC realisations.

[30] Demand minus supply from non-dispatchable generation resources (e.g. wind and PV).
[31] Gonzato, S., Bruninx, K., Delarue, E.: The effect of short term storage operation on resource adequacy.

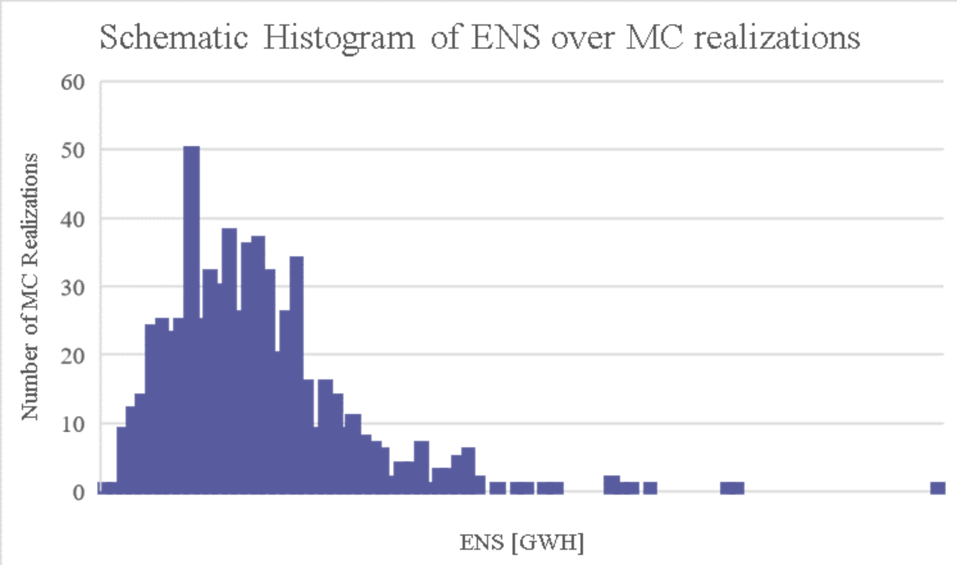


Figure 23: Schematic histogram of the ENS over 525 MC realisations

Note: Each histogram bin covers a range of 5 GWh ENS and contains the number of MC realisations that lie within the respective ENS range.

To obtain robust results, the impact of additional MC realisation results on the existing results should be small or negligible and thus have limited/no impact on the convergence metrics. It can then be said that the model has converged.

In ERAA 2025, the convergence of the adequacy results is calculated in several steps. Following a set of model runs, the models' convergence is assessed and, if the convergence is not reached, additional simulations using new FO realisations are launched, increasing *M*.

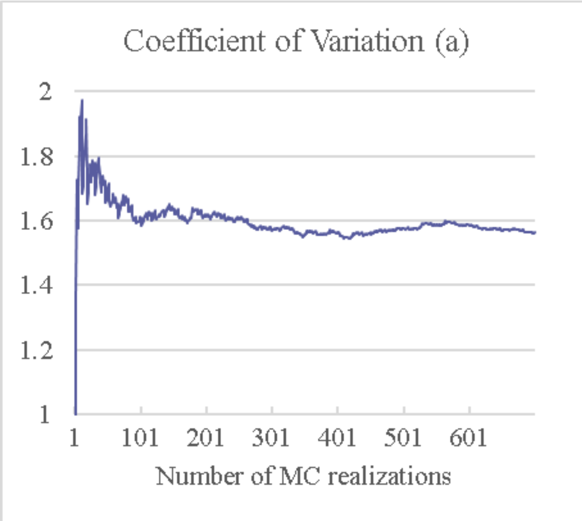
The convergence of the models is assessed using the relative change of the coefficient of variation α derived from the ENS of the entire geographical scope, as defined by Eq. (3):

$$\alpha = \frac{\sqrt{\mathrm{Var}[EENS])}}{EENS}, \qquad (3)$$

where $EENS$ is calculated over all MC realisations completed at the moment of assessment and $\mathrm{Var}[EENS]$ is the variance of the expectation estimate (i.e. $\mathrm{Var}[EENS] = \frac{\mathrm{Var}[ENS]}{N}$).

The left side of Figure 24 provides an example of how the coefficient of variation of an MC model evolves and changes relative to the number of MC realisations. No significant changes in α occur past a certain number of MC realisations, meaning that no significant changes in averaged results are expected and thus no additional MC realisations are needed to improve the results. No explicit simulation stopping criterion is set for α. The decision whether to launch additional model runs is based on a compromise between the relative change in α and the required computational time. Annex 3 offers insight into the coefficient of variation and its relative change versus the increasing number of MC simulations for the different ERAA 2025 scenarios.

The right side of Figure 24 provides an example of the evolution and relative change of the coefficient of variation of an MC model as a function of the number of MC realisations. No significant changes occur past a certain number of MC realisations, meaning that no significant changes in averaged results are expected and thus no additional MC realisations are needed to improve the results.



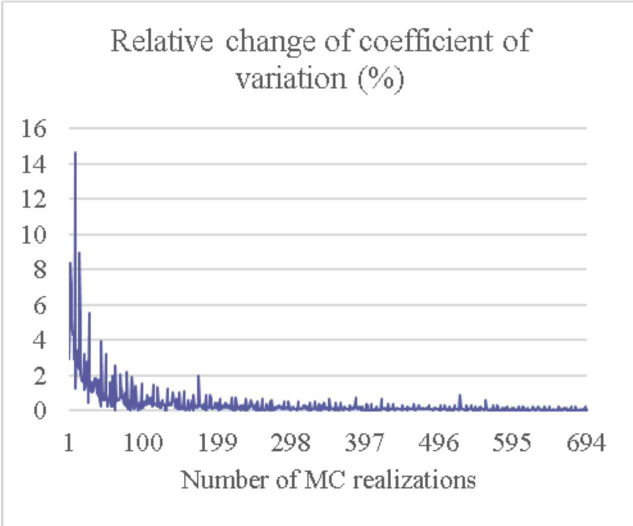


Figure 24: Example of α evolution and its relative change with an increasing number of MC samples for a converging model

Certain inputs and parameters can have a significant impact on the results of those adequacy indices and their convergences, including:

- hydro power modelling;
- commercial exchanges between countries;
- the use/absence of extreme, yet realistic, historical WSs;
- outages and their modelling, including both maintenance outages and FOs[32]; and
- the number of units with outages in a country (more units lead to faster convergence).

11.7 Local matching and Curtailment Sharing

Local matching (LM), curtailment minimization, and curtailment sharing are components of the EUPHEMIA algorithm (PCR market coupling algorithm) which are modelled to some extent in the ERAA. The consideration of the EUPHEMIA principles within the ERAA methodology are discussed in Section 11.7.5. Transposition of the EUPHEMIA rules in ERAA requires some simplifications and methodological choices due to the different context in which EUPHEMIA market coupling and adequacy studies like ERAA are conducted.

[32] To understand the impact of FOs – which are random by definition – it is important for all of the tools to use one commonly agreed upon maintenance schedule. This maintenance schedule should respect the different constraints specific to the thermal plants in different countries, as provided by TSOs.

11.7.1 Flow factor competition

In EUPHEMIA, local matching, minimisation and sharing rules intervene when there is "non-acceptance" of price taking orders (PTOs) in one or several bidding zones, i.e. "pay any price" orders which are valued at the market price cap. Non-acceptance of PTOs of demand can be considered equivalent to having ENS in the ERAA simulations. Local matching constraints are used in the operational EUPHEMIA market coupling algorithm to first match local demand and generation within a bidding zone, to set minimum acceptance volumes of PTOs. Furthermore, curtailment mitigation, minimisation, and sharing rules are used in the operational EUPHEMIA market coupling algorithm to mitigate the effect of flow factor competition (FFC) on the "non-acceptance" (curtailment) of price demand taking orders. A detailed description is provided below.

If two possible market transactions generate the same welfare, the one with the lowest impact on the scarce transmission capacity will be selected first within FBMC. This also means that some buy (demand) bids with higher prices than other buy (demand) bids located in other study zones might not be selected within the FB allocation to optimise the use of the grid and maximise total market welfare. This is a well-known and intrinsic property of flow-based market coupling (FBMC) referred to as FFC.

Under normal FBMC circumstances, FFC is accepted, as it leads to maximum overall welfare. However, for the special case where the situation is exceptionally stressed – e.g. due to scarcity in one or several bidding zones – FFC could lead to a situation where PTOs curtailment takes place non-intuitively or non-fairly. For example, this could mean that some buyers (orders in the market) ready to pay any price to import energy would be rejected, with lower buy bids in other study areas selected instead due to FFC.

11.7.2 Local matching

LM is achieved in EUPHEMIA through the LM constraint. EUPHEMIA enforces the LM of price-taking (buy) hourly orders with hourly orders from the opposite sense (sell) in the same study zone as a counterpart. That means that local PTOs are prioritised and matched with local supply, whenever the curtailment of PTOs can be avoided locally on an hourly basis. This sets the minimum number of PTOs accepted in the system. In EUPHEMIA, the LM constraint is relaxed in the CS step, allowing the curtailed PTOs of each bidding zone to deviate in both directions from the LM result.

The LM constraint is enforced for all study zones of ERAA models in the welfare maximisation problem (curtailment mitigation) and in the curtailment minimisation step (see Figure 25 below).

11.7.3 Curtailment mitigation, minimisation, and sharing

To address FFC issues concerning PTOs, EUPHEMIA implements the curtailment mitigation, minimisation, and sharing principles. These principles aim to minimise curtailment and equalise the curtailment ratios between the bidding zones (willing to share curtailment according to current market rules) that are simultaneously in a curtailment situation (having an electricity price at the price cap) and those that are configured to share curtailment as much as possible. In other words, these curtailment principles aim to minimise and "fairly" distribute the curtailment (rejection of PTOs) across the involved market zones by equalising the curtailment ratios of each zone, defined as curtailed PTOs divided by the total volume of local PTOs, as much as possible and while respecting FB and NTC constraints.

11.7.4 Adequacy patch steps

The aforementioned steps, as implemented within EUPHEMIA in the SDAC (adequacy patch), are summarised in Figure 25.

Figure 25: Steps of the adequacy patch in SDAC

The first phase involves steps applied at the start of the SDAC market clearing algorithm. First, LM constraints aim at avoiding unnecessary domestic curtailment by enforcing that simple divisible bids match in priority with local PTOs.

Second, a penalty is introduced in the welfare maximisation objective function that prioritises the minimisation of curtailment in bidding zones with the highest curtailment ratios, defined as:

$$CurtailmentRatio = 1 - \frac{accepted\ price\ taking\ orders\ volume}{submitted\ price\ taking\ orders\ volume}$$

The curtailment ratios are used in the “max penalty term” added to the welfare maximisation objective function as such:

$$-M \sum_{h} MaxCurtailmentRatio_h$$

With $MaxCurtailmentRatio$ being the largest curtailment ratio across the modelled bidding zones. Provided that the value of M is sufficiently large, EUPHEMIA will effectively prioritise the minimisation of this ratio over the welfare maximisation.

Hence, the first phase of the SDAC adequacy patch equalises the curtailment ratios between bidding zones under the constraints of LM rules. It can lead to an increase or decrease of curtailment in each bidding zone, but also in the total system level of curtailment.

The second phase of the SDAC adequacy patch consists of post-processing the main welfare optimisation run. The post-processed curtailment minimisation tends to further minimise curtailment, expressed as:

$$Min \sum_{z,h} (accepted\ price\ taking\ orders\ volume)\,(1-x)^2$$

With x being the ratio between the accepted and submitted PTO volumes.

In this step, even if the total welfare would remain fully unchanged, the total curtailment can still vary. This requires the existence of alternative solutions with identical system costs but different total ENS values. This occurs when the increased costs due to an increase in ENS are exactly offset by savings in generation costs, resulting in no net change in overall system costs.

Within this second phase, the difference between Step 3 (curtailment minimization) and Step 4 (CS) is that in Step 4, the LM constraints are relaxed for countries willing to share curtailment (i.e. a parameter in EUPHEMIA settings).

An example of the functions of the adequacy patch steps described in Figure 25, is provided in Figure 26 below:

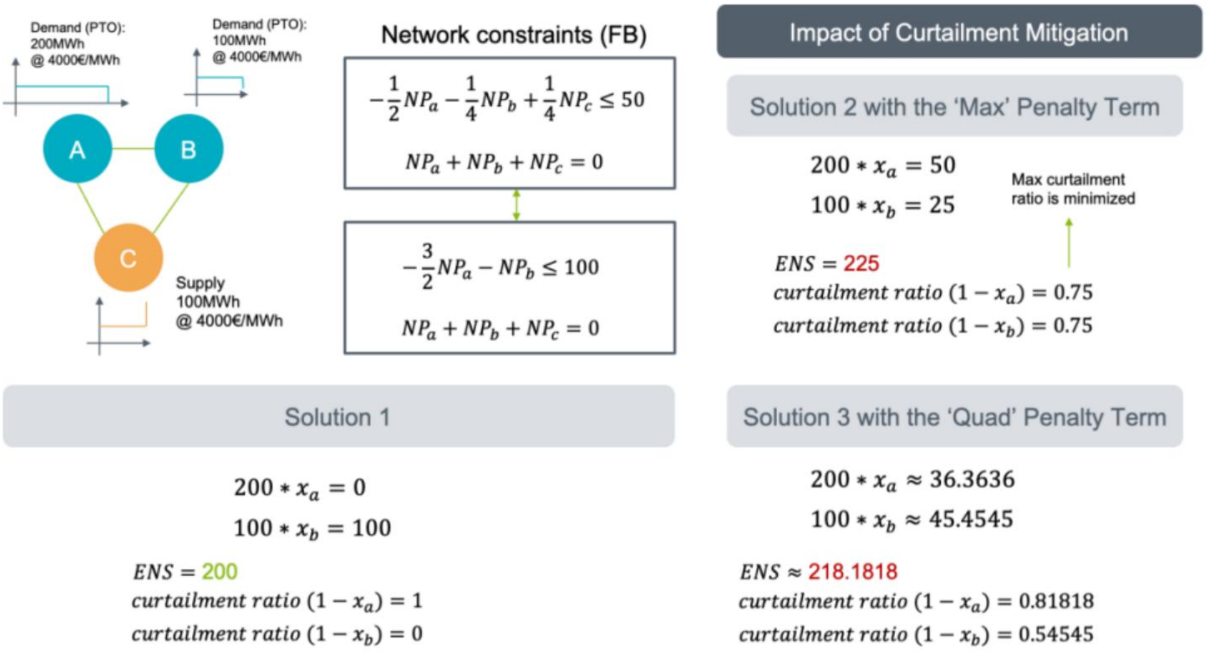


Figure 26: Example illustrating the functioning of the SDAC adequacy patch

Solution 1 minimises the ENS (bottom left of Figure 26). In this example, all solutions lead to the same system cost because the marginal costs of not meeting the demand are exactly equal to the marginal generation costs. This enables increased focus on some specific impacts of Steps 2 and

3, while parking the question of the detailed degrees of freedom allowed in the post-processing Phase 2, composed of Steps 3 and 4. Step 2 (curtailment mitigation) of the adequacy patch, corresponding to the penalty terms in the welfare objective function, will first lead to Solution 2, where the total ENS is increased compared to Solution 1 without the application of the penalty term. Step 3 (curtailment minimisation) ultimately leads to Solution 3. Step 4 (CS) which differs from Step 3 only by having LM constraints relaxed, is not considered here, since it would not make any difference in this example. In this example, Solution 2 leads to an increase of the ENS of 25 MW (12.5%) compared to Solution 1, while in Solution 3, the ENS is increased by 18.18181MW (9%).

11.7.5 Implementation in ERAA

To replicate the EUPHEMIA adequacy patch, the curtailment mitigation, minimisation, and sharing principles are implemented as an integrated post-processing procedure.

Therefore, ERAA performs an ED (adequacy model) optimization with LM constraints included, but without curtailment mitigation. Then, a post-processing run is applied to model mitigation and CS. "Sanity checks" are performed to monitor the proper application of the principles.

ED run

LM constraint:

In the ERAA, the LM constraint is implemented in the ED run as a conditional constraint following two different rules:

1. Each study zone is allowed to export only the share of generation capacity exceeding its internal demand, hence, preventing net exporting study zones from having ENS.
2. Net importing study zones should primarily use internal resources to cover internal demand, avoiding exports to other study zones driven by better FFC.

The LM constraint is enforced for all study zones in the welfare maximisation problem, the condition of activating the surplus of generation in a study zone compared to the demand of the study zone for a specific hour.

Mathematically, the condition is written as:

$$If\ NetPosition_{StudyZone} - ENS_{StudyZone} \geq 0\ or \sum Line_{Flows} - ENS \geq 0$$

Mathematically, the constraint is written as:

$$NetPosition_{StudyZone} + Load_{StudyZone} - Generation_{StudyZone} \leq 0\ or \sum Line_{Flows} + Load_{StudyZone} - Generation_{StudyZone} \leq 0$$

FFC conditional constraint:

In addition to the LM constraint, an FFC constraint is implemented in the ED run to ensure that the ENS for a specific study zone does not exceed the allowed unserved energy defined by the so-called "domestic energy not served" (DENS), i.e. the difference between domestic load and generation, due to FBMC.

Two situations tend to occur due to the implementation of the FBMC constraints:

1. ENS can be created for net exporting study zones to find the lowest ENS for the FB region as a whole; and
2. study zones with low “flow-factors” are penalized with ENS to the benefit of study zones with high “flow-factors”, even when all such study zones are simultaneously at the maximum market price cap.

Mathematically, the condition is written as:

$$If\ NetPosition_{StudyZone} - ENS_{StudyZone} < 0\ or \sum Line_{Flows} - ENS\ < 0$$

Mathematically, the constraint is written as:

$$NetPosition_{StudyZone} \leq 0\ or \sum Line_{Flows} \leq 0$$

Post-processing

The post-processing run is designed to take the solution of the ED run and ensure the equalisation and minimisation of curtailment ratios (called CS distribution) while ensuring that all grid constraints and local matching are respected.

The LM and FFC constraints in the post-processing run are based on the DENS inherited from the ED run. The DENS can be simply defined as demand minus generation for each study zone individually. Therefore, the LM is active if the DENS ≤ 0 and the FFC constraint will ensure that ENS ≤ DENS.

As the proxy for the PTO volume equals the DENS, to share the ENS within the different study zones (i.e. the ones willing to share curtailment according to EUPHEMIA rules), a penalty involving a quadratic function is added to the objective function, defined similarly to EUPHEMIA as follows:

$$\boldsymbol{DENS} * (\frac{ENS}{DENS})^2$$

The penalty grows quadratically with increased curtailment, and hence equilibrium can be expected where curtailment ratios are equalised, while perfect equalisation of curtailment is limited due to the existing grid constraints, similarly to the EUPHEMIA adequacy patch.

11.7.6 Considerations on implementation in ERAA 2025

It is important to note that in EUPHEMIA, relaxing LM in Step 4 for all bidding zones at the price cap can result in net exporting and net importing bidding zones participating in CS, and having ENS post-CS. This behaviour is not replicated in ERAA, as LM constraints are kept as they were implemented in the ED model. Thus, ERAA CS results contain no net exporting study zones with ENS, and only ENS is present in those study zones that are net importing and that without imports, assuming fixed ED dispatch, would have their ENS = DENS. The net positions during scarcity can be observed as part of the detailed results analysis included in Annex 4.

There is currently no direct and straightforward approach to link the volumes of inflexible demand in ERAA simulations and the corresponding expected PTOs volume to be traded within the (future) DA market. Based on historical observed traded PTOs, their relationship and volume with respect to the total native demand may vary significantly between study zones.
For ERAA 2025, the proxy for PTOs chosen is the DENS. This is one of the key methodological choices mentioned at the beginning of the chapter, as part of the current CS implementation in ERAA. In the DA auctions, however, the PTOs as defined in the Euphemia Adequacy Patch as part of the curtailment sharing step is the precise volume of price taking orders and not the local difference between demand and supply. As we do not have discrete buy and offer volumes attached to a specific bid price in ERAA, the choice of PTOs proxy requires some necessary simplifications and assumptions. Detailed additional validations of the complex CS methodology implementation are continuously ongoing to improve robustness and stakeholders' understanding of the CS modelling features.

Finally, in EUPHEMIA, the net position of importing and exporting bidding zones can change in Steps 3 and 4, but only for bids that are “at the money” after Step 2. Clearing prices can’t change in Steps 3 and 4 compared to Step 2. Although LM is relaxed in Step 4 of the algorithm in EUPHEMIA, its relaxation must be considered together with the “at the money” rule mentioned above. Generator dispatch is given downward flexibility in the post-processing steps of ERAA to capture these principles as accurately as possible, but without the “at the money” principle being used and enforced.

11.7.7 Sanity checks

As the application of the CS feature in the ED occurs in all hours and WSs performed with ENS pre-CS, thousands of hours must be analysed for robustness and quality. For this purpose, automatic sanity checks have been implemented in ERAA 2025.

These sanity checks monitor pre- and post-CS values of demand, generation, net positions, DENS, and ENS. For study zones with positive DENS, the KPI (1 − x) can be computed to use in the proxy of EUPHEMIA’s quadratic penalty term, with x being the ratio between the DENS pre-CS and the net imports pre- or post-CS (i.e. proxy to the “accepted” PTOs).

Given that the EUPHEMIA adequacy patch minimises and equalises (1 − x) ratios, monitoring (1 − x) ratios pre- and post-CS confirms the robustness of the feature, as the sanity checks verify:

1. The level of achievement of the equalisation of (1 − x) across study zones with positive DENS.
2. The effect of the active FB constraints on the redistribution of ENS, assessing whether equalisation is limited by active FB constraints.
3. The corresponding increase of the total system ENS in relation to the impact of active FB constraints mentioned above.

To demonstrate the functioning of CS and the effects of FB constraints, the following table shows relevant data points for the CS model from a single hour where there was ENS after the ED model was run (post-ED). For simplicity, only study zones with positive ENS before or after CS are shown. The selected hour comes from 2030 ED simulation results, with the enhanced hurdle premium combined with the revenue cap risk-aversion approach: WS32, FO sample 4, on 14/12/2030 at 22:00:

Table 17: Single hour example of curtailment sharing

Study Zone	Load (MW)	Generation (MW) – pre-CS	ENS (MW) – pre-CS	Generation (MW) – post-CS	ENS (MW) – Post-CS	DENS (MW)	ENS (MW) – FBMC Relaxation
BE00	13,869.73	9,218.17	0.00	9,218.19	2,377.39	4,651.57	2,355.58
BG00	5,378.56	4,839.04	0.00	4,839.06	204.43	539.52	273.22
CZ00	8,027.72	7,345.03	0.00	7,345.05	271.44	682.69	345.72
DE00	88,863.79	66,018.15	20,343.75	66,018.17	12,072.09	22,845.64	1,1569.19
DKE1	2,841.91	1,532.33	0.00	1,532.35	635.06	1,309.58	639.21
DKW1	4,895.84	3,318.40	332.94	3,318.42	819.43	1,577.44	798.83
ES00	41,567.14	34,054.65	5,862.36	34,054.67	3,783.17	7,512.48	3,804.37
FR00	83,609.00	73,926.20	1,473.06	73,926.22	4,888.82	9,682.80	4,903.43
GR00	6,532.77	6,296.02	0.00	6,296.04	89.71	236.75	119.89
GR03	354.18	56.18	0.00	56.21	112.91	297.99	150.90
HU00	6,824.90	5,892.39	0.00	5,892.41	351.48	932.51	472.23
ITCN	3,235.78	2,328.88	607.38	2,328.90	451.18	906.90	459.26
ITCS	6,757.52	4,434.54	0.00	4,434.56	1,155.69	2,322.98	1,176.37
ITS1	3,046.07	2,398.85	0.00	2,398.87	321.99	647.22	327.76
ITSI	2,527.61	2,114.78	0.00	2,114.80	205.38	412.83	209.06
NL00	22,684.90	18,712.89	1,291.17	18,712.91	2,048.01	3,972.01	2,011.45
SI00	2,317.46	1,948.86	0.00	1,948.88	144.58	368.59	186.66
UK00	47,473.32	45,771.41	755.82	45,771.43	755.82	1,701.91	755.82
ES00-MA00	135.00	0.00	135.00	0.00	135.00	135.00	135.00

The typical effect of FFC can be observed in the “pre-CS” results, with all the ENS allocated in few study zones after the initial ED run. After the CS post-processing step, ENS is distributed to study zones with DENS. ENS after CS is distributed as “proportional” to DENS as possible, given FB constraints. Below is a table showing the curtailment ratios (CR) pre- and post-CS as defined by the ratio of the square of ENS divided by the square of DENS for each study zone.

Table 18: Curtailment ratios with and without relaxed flow based constraints

Study Zone	CR – Pre-CS	CR - Post CS	CR - Post CS with FB Relaxation
BE00	0.00	0.51	0.51
BG00	0.00	0.38	0.51
CZ00	0.00	0.40	0.51

DE00	0.89	0.53	0.51
DKE1	0.00	0.48	0.49
DKW1	0.21	0.52	0.51
ES00	0.78	0.50	0.51
FR00	0.15	0.50	0.51
GR00	0.00	0.38	0.51
GR03	0.00	0.38	0.51
HU00	0.00	0.38	0.51
ITCN	0.67	0.50	0.51
ITCS	0.00	0.50	0.51
ITS1	0.00	0.50	0.51
ITSI	0.00	0.50	0.51
NL00	0.33	0.52	0.51
SI00	0.00	0.39	0.51
UK00	0.44	0.44	0.44
ES00-MA00	1	1.00	1.00

In this example, FB constraints naturally prevent perfect equalisation of curtailment ratios. An experiment was run to relax FB constraints in both the Nordic and Core FB regions, which led to near-perfect equalisation of curtailment ratios, thus confirming the robustness of the CS step as well as the impact of existing market coupling constraints which are correctly respected. Curtailment ratios are equalized to the extent possible, with the exceptions of areas that do not participate to CS, such as UK00 and ES00-MA00 (i.e. MA00 is a non-explicitly modelled study zone excluded from CS).

12 Databases and tools used for the ERAA

The ERAA methodology uses data collected from TSOs, generated by internal tools using TSO assumptions/data and solutions co-developed with other entities. The following sections describe the databases and tools used in the ERAA assessment. These databases are commonly used with other ENTSO-E assessments such as the Ten-Year Network Development Plan (TYNDP), Seasonal Outlook, etc.

12.1 Market modelling database (PEMMDB)

ENTSO-E uses a single source of supply-side and grid data across all its assessments: the PEMMDB, containing data collected by TSOs on plant NGC, interconnection capacities, generation planned outages, etc. The database is aligned with national development plans and contains data about the power system based on the best knowledge of the TSOs at the time of data collection. The PEMMDB contains a highly granular unit-by-unit resolution of European power plants, their technical and economic parameters, their expected decommissioning dates, and the forecasted development of RES capacities. Moreover, it provides an hourly time series of must-run obligations in addition to the derating of thermal units.

12.2 Demand forecasting toolbox

ENTSO-E centrally creates hourly demand profiles for most European countries using a temperature regression and load projection model incorporating uncertainty analysis under various climate conditions. The DFT comes in a software application developed by an external provider (Sia Partners). It is important to mention that some TSOs have provided their own demand time series to be used by ENTSO-E, using their own DFT.

The purpose of the report is to provide the audience with a transparent view hourly demand forecasting methodology and input data key assumptions used in ERAA 2025. Pushed by the introduction of the ERAA methodology, ENTSO-E was required to develop a unique tool that would undertake high-quality electricity demand forecasting and profiling for all ENTSO-E studies (i.e. short, medium and long-term).

Section 12.2.1 explains the DFT methodology. The hourly demand time series are created based on historical load data, weather variables,[33] calendar data, and technology diffusion and are adjusted to meet national estimates TSO's targets for average annual energy.

Sections 12.2.2, 12.2.3, and 12.2.4 explain the methodology used by Poland, Belgium, and France, which follow different methodologies given internal TSO tools.

[33] The modelling is performed with (irradiance, windspeed and population weighted temperature) historical years 1982–2023 and forecasted in projected years 2025–2036 from three different models, as recommended by ET Climate of Data & Models.

12.2.1 Hourly demand forecasting methodology

Introduction

For the creation of hourly load profiles for most European countries, ENTSO-E uses a load forecasting toolbox that incorporates uncertainty analysis under various climate conditions. The toolbox comes in a software application developed by an external provider. It is important to mention that the ERAA 2025 Member States could have also provided their own hourly demand time series directly to ENTSO-E using alternate methodologies (for details, please see Sections 12.2.2, 12.2.3, and 12.2.4).

The forecasting toolbox (DFT) enables easy electric load prediction starting from data analysis of historical time series (electric load, temperature, climatic variables and other). It is an advanced forecasting tool that leads to a stronger harmonisation of forecasting activities and comparability of their outcomes provided by ENTSO-E members.

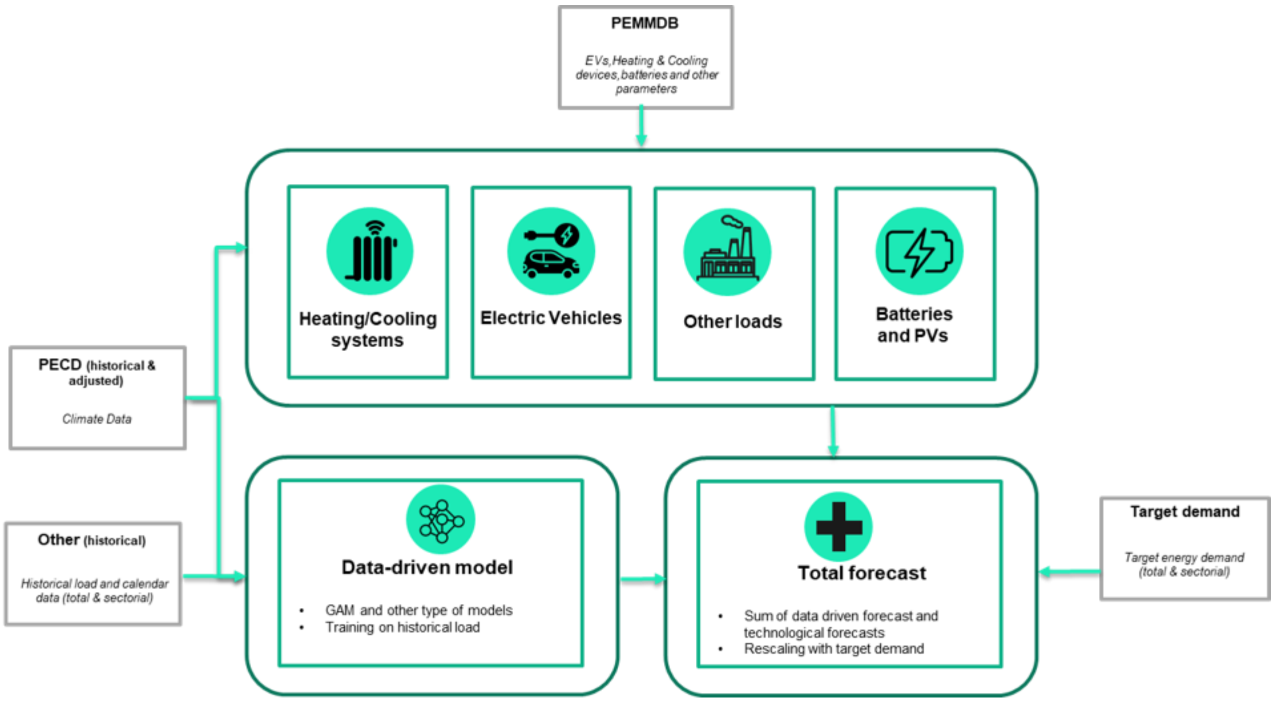


Figure 27: Overall demand forecasting process applied by the DFT

Figure 27 shows the overall demand forecasting process applied by the DFT. A more detailed description of input data, methodology and consistency checks is provided in the following document. However, batteries and PVs are modelled separately (i.e. not in the DTF) as shown in the figure above. Additional information is provided below.

DFT approach: data-driven load prediction

The DFT tool was developed to address the problem of electric load prediction based on temperature and other climatic variables. More precisely, the tool is meant to provide an estimate of the daily load profile based on historical data of the load and the climatic variables and calendar effects on the load. In addition, the tool was prepared to perform load adjustment to consider the evolution of the electrical market, such as the penetration of HP technology, the increase in EVs, batteries, the evolution of the base load, etc. The DFT was developed as a general forecasting platform while also allowing proper customisation for its diverse user base. So, it provides a common methodology but at the same time allows the specificities of market nodes, new technologies, and expert knowledge to be incorporated into its predictions.

This introduction focuses on the problem of load prediction based on historical climatic data and calendar effects. To address this, machine learning methodology was developed and implemented in the DFT.

A general overview

The DFT contains three different algorithms for modelling hourly electric load time series. These are popular machine learning algorithms that can provide precise estimates of future load curves. At the same time, these methods can give interpretable results, allowing the main drivers of load evolution to be inferred. Currently available algorithms in the DFT:

- Generalised additive models (GAMs)
- Random forest
- Linear regression

learning methodology has been devised and implemented in DFT.

1. GAM

In statistics, a GAM is a linear model in which the linear response variable depends linearly on unknown smooth functions of some predictor variables, and the interest focuses on inference about these smooth functions. The model relates a univariate response variable, Y, to some predictor variables, xi. An exponential family distribution is specified for Y (for example, normal, binomial, or Poisson distributions) along with a link function g (for example, the identity or log functions) relating the expected value of Y to the predictor variables via a structure such as:

$$g(E(Y)) = \beta 0 + f1(x1) + f2(x2) + \ldots\ldots + fm(xm)$$

Since all regressors are independent in GAMs, the model can compute the different regressors simultaneously, which allows a very quick fitting time. Because of the independence between regressors, we can easily infer the impact of each predictor variable on the prediction. Depending on the type of regressors, we can have a continuous dependence plot or non-continuous ones for categorical features.

2. Random Forest

Similar to GAMs, random forest consists of non-parametric models that explore different nonlinear possibilities for the relationships between Y (explained variables) and X (explanatory variables). Apart from that, it is a very different modelling approach that originates from simple decision tree models. To put it simply: every tree (estimator) takes a random subset of training samples along with a random subset of variables (features). Then, the algorithm applies and searches for the optimal decision rules based on selected goodness-of-fit measures. As a regularisation step, a complex aggregation of the trees (estimators) is used to avoid overfitting.

3. Linear regression

Regression analysis is a statistical methodology that allows us to determine the strength and relationship between a set of variables. The results from the regression help in predicting an unknown variable depending on its relationship with the predicting variables.

A linear regression can be written as:

$$y = \beta.X + \varepsilon \text{ , with } \beta = \beta 0 + \beta 1 + \beta 2 + \ldots + \beta n \text{ and } X = 1 + X1 + X2 + \ldots + Xn$$

where, y is the observed values, β is the linear coefficient, X is the set of variables and ε the error. β is calculated using the ordinary least squares method which minimises the quadratic error between the prediction and the observations.

Set of predictor variables
The algorithms in the DFT accept the following predictor variables, allowing users the freedom to choose which ones to include:

- Climatic variables from the PECD database (temperature, wind speed, irradiance)
- Seasonality and trend components (day-of-year, day-of-week, month, etc.)
- Special calendar effects (different user-defined group of days)

Model selection
Another feature of the DFT is the model selection process, which is designed to make it easy for users to select the best-fitting data-driven model based on several objective metrics. These performance indicators make it possible to assess the forecasting performance of the estimated models. The metrics include RMSE, MAPE, cross-validated RMSE, and cross-validated MAPE for both the training and the test set.

DFT approach: electric load correction

In addition to a load prediction based on climatic variables (and groups of days), the DFT allows the user to correct these predictions based on information and estimates about other load components. In particular, users have the option to include predictions about:

- electric vehicles;
- sanitary water demand;
- air conditioning demand (cooling);
- cooling HP demand;
- heating HP demand;
- hybrid heating HP demand;
- additional base loads; and
- energy demand increase.

Electric vehicles

EV consumption is modelled using a deterministic physics-based model. The total EV load for a specific forecast year is calculated using the following formula:

$$Total\ Load = \sum_{e}^{EV\ types} \sum_{d}^{Day\ types} \sum_{c}^{Charging\ types} Additional\ number\ of\ vehicles_{(e)} * average\ effective\ usage_{(e,d)} * efficiency_{(e)} * load\ distribution_{(e,d,c)} * charging\ fraction_{(e,c)}$$

The load values are calculated for each type of load, type of day and type of vehicle and then summed.

HPs, air conditioners, hybrid HPs, sanitary water

Basic logic

From a high-level perspective the same basic methodology applies to all of these technologies, and in this section, they are sometimes referred to collectively as HP methodology.

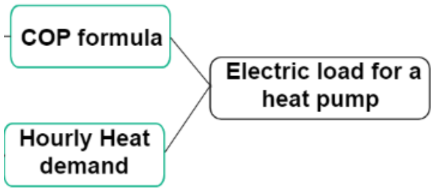


Figure 28: Heat pump load break down

As shown in Figure 28, the HP methodology has two underlying bricks that calculate the heat demand for heating and sanitary water on one side, and the coefficient of performance ((COP) efficiency of the HP) on the other side.

The final electric load for one specific type of HP is computed as by dividing heat demand by COP:

$$electric_{load} = \frac{heat_{demand}}{COP}$$

This electric load is then multiplied by all the additional number of HPs for each category (brand new units of HP for heating for example) from the reference year to the forecasted year. Finally, all the categories of HPs are summed to obtain the total load of all HPs.

Exception: for HPs that replace electric heaters (or water heaters/cooling systems), the DFT subtracts heat demand for this specific HP from the electric load that was previously calculated. This allows the switch to a more efficient technology to be reflected in the results.

$$electric_{load,hp\ replacing} = \frac{heat_{demand}}{COP} - heat_{demand}$$

Underlying methodology

Both heat demand and COP are calculated based on best practices from the related literature and publicly available databases (When2Heat, ENTSO-E Transparency Platform). A more comprehensive overview of the methodology is shown in Figure 29 below.

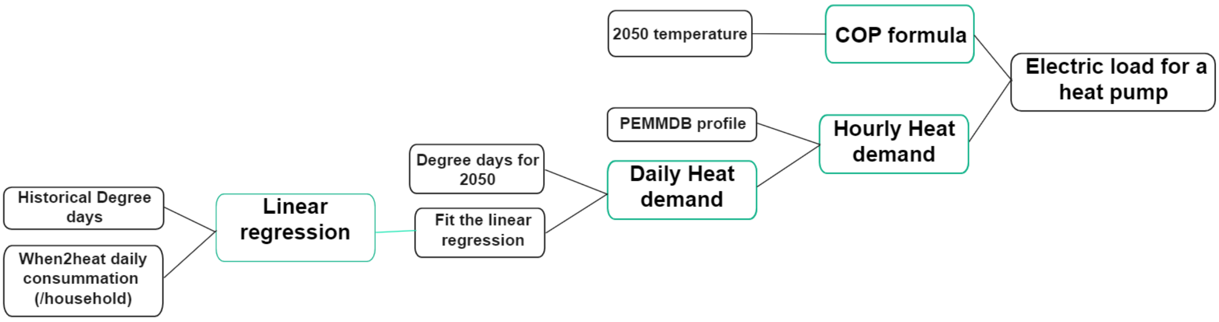


Figure 29: Heat pump modelling

To obtain the daily heat demand for every market node and HP type, a historical analysis was carried out. This analysis is based on the heating degree days (HDD) and cooling degree days (CDD) concept. HDD and CDD are linked to the daily heating and cooling demand of a household through a linear regression. This relationship is then transferred to future climatic scenarios to obtain a predicted daily heat demand for every HP type.

As a final step to obtain hourly heat demand, the user-defined daily profile is used for hourly modulation of HP demand.

To obtain the estimated hourly COP time series, the tool assumes a functional (quadratic) relationship between the sink and source temperature difference and the actual COP of the specific HP. This COP function is cut below a 15 °C temperature difference. In addition, a constant correction factor (0.85) is applied to the calculation at the end to account for real-world loss effects.

Further information about the underlying methodology can be found in the online documentation for the tool.

Batteries

Since the contribution of behind-the-meter (btm) generation on the overall load is expected to be significant, the DFT load time series is further processed to account for btm battery storage and rooftop PV. The input data needed is limited to the DFT output as well as installed capacities of rooftop PV and btm battery storage systems, both coming from PEMMDB.

Further, different model settings are implemented to mimic various prosumer behaviours. The output of the btm model has a load-reducing effect on both the sum of overall demand and on peak load.

PV computation

The first step is to compute how much energy is produced by the PVs for the market node. This is equal to the calculation of the available capacity of PV in Plexos.

Steps:

- Read the rooftop PV capacity factors from the PECD database.
- Obtain the total installed PV capacity from PEMMDB.
- Estimate the total PV production as total PV power multiplied by the normalised irradiance.

Since the contribution of behind-the-meter generation on the overall load is expected to be significant, the DFT load timeseries is further processed to account for behind-the-meter (btm) battery storages and rooftop photovoltaics. The input data needed is limited to the DFT output as well as installed capacities of rooftop photovoltaics and btm battery storage systems, both coming from PEMMDB.demand sum as well as on peak load.

Batteries

Once rooftop PV production is computed, we can compute battery usage. The btm model is an optimisation approach for btm battery dispatch. Its behaviour is adjusted using a set of parameters allowing for different operation types, like *greedy* behaviour, *auto-consumption-orientated,* or *load-shifting*.

The optimisation interval is by default set to 24 hours and equals perfect foresight. The objective function, in its essence, is formulated as follows:

$$maximize \sum_{i}^{interval} (c_i * x_i - p_1(x_i) - p_2(x_i))$$

In the model formulation, c_i stands for an incentivising term driving the battery dispatch x_i. In the current implementation, a flexible formulation of residual load is used for c_i to avoid depending on exogenous price signals in the modelling pipeline. The terms $p_1(x_i)$ and $p_2(x_i)$ resemble penalty terms to fine-tune the model behaviour.

Further information about the btm model can be found in the corresponding publication.[34]

Energy demand

It is possible to apply an energy growth/decrease to the baseload based on user-defined inputs. For this feature, the sum of all the energy growth/decrease between the reference year and the forecasted year is computed and applied to the baseload.

Target demand rescaling

A rescaling methodology was developed to comply with the target demand requirements provided by the user for a given TY and market node.

The rescaling is performed by applying a constant rescaling ratio to the raw load curves. The rescaling ratio is computed using the difference between the expected target demand input by the user and the annual sum of the raw forecasts calculated by the DFT.

Technically, the rescaling is done in three steps:

- First, a rescaling ratio for HPs is computed and rescaled load curves for HPs are obtained.
- Second, a different rescaling ratio for baseline demand is computed based on the remaining target demand (not covered by the rescaled HP demand).
- Then rescaled load curves for baseline is obtained.
- Finally, the total rescaled load curve is obtained by summing the load curves that are supposed to be rescaled with the load curves that are not supposed to be rescaled.

[34] Flexible Behind-the-Meter Battery Storage Model for Enhanced Mid-to Long-Term Load Forecasting | IEEE Conference Publication | IEEE Xplore

Further information about these discharging methods can be found in the online documentation for the tool.

Peak demand rescaling

There are three different peak adjustment options available in the tool.

1. Peak adjustment: limit option

The limit option uses a parameter called load_factor to guess the highest expected value (max expected peak value) for the forecast year at the selected market node. This highest expected value acts as a benchmark to determine whether the predicted peaks are too high or too low. If some peaks are above this benchmark, they should be reduced; if they are below it, they should be increased. This adjustment is made to keep the total energy the same while fine-tuning the peak values.

The load factor is calculated separately for each market node as:

$$\frac{\max\_peak}{raverage\_daily\_energy}$$

where max_peak is the highest measured peak value and average_daily_energy the mean of the 24 energy values calculated for the studied day. The load_factor is calculated for every project separately using the historic load values of each market node on the calendar_load_weather_data file generated with each data_loading job. This way, the load_factor will have a value that takes into account the specificities of the data imported by the TSO. For each year, we calculate the load_factor for the days having load values superior to the quantile (0.97). The final load_factor is the average of all the calculated values.

Calculation

The maximum expected peak value is calculated using the forecasted load values and the load_factor. We identify the day with the maximum forecasted peak value and calculate its average daily energy. We then obtain:

$$max\_expected\_peak = average\_daily\_life * load\_factor$$

The adjustment of the predicted load values is made by multiplying the values that must be redressed by the adjustment_factor calculated as:

$$\text{adjustment\_factor} = \frac{max\_expected\_peak}{max\_peak}$$

For the remaining options, the peaks to be obtained are based on values given by the TSO on the PEMMDB file. The adjustment made here will be applied to the total prediction first then to the baseline prediction.

2. Peak adjustment: force option with mean

For this option, the target peak value set by the TSO will be achieved on average. If only one climatic scenario was selected, the corresponding peak for this simulation would be equal to the target peak set in the PEMMDB file. However, if more than one climatic scenario was selected, the average of their adjusted peaks would be equal to the target set.

To calculate the target peak for each climatic scenario for a specific forecast year, we consider the target peak set for the said forecast year, along with the list of all the predicted peak values across the selected climatic scenarios. The target of the ith climatic scenario for this option is equal to:

$$ith\_climatic\_scenario\_target\_peak = \frac{ith\_forecasted\_year * target\_peak}{\frac{1}{n}\sum_{j=1}^{n} jth\_forecasted\_year * target\_peak}$$

with n the number of climatic scenarios selected.

To adjust the total prediction, we employ the same methodology as the Limit option. This involves calculating the adjustment factor using the calculated target peak and the current forecasted peak value.

Once this is done, we adjust the baseline forecasts under the constancy of the technological forecasts assumption as such:

$$\begin{aligned} rescaled\_and\_adjusted\_baseline \\ &= rescaled\_and\_adjusted\_total\_prediction \\ &- adjusted\_total\_rescaled\_before\_adjustemtnt + rescaled\_baseline \end{aligned}$$

3. Peak adjustment: force option with max
This option closely resembles the second, with two distinctions:

The target peak set by the TSO for the forecasted year is achieved at maximum. This implies that across all climatic scenarios, the adjusted peaks remain below or equal to the target.

The calculation of the target peak corresponding to the ith climatic scenario differs from the second option: instead of using the mean of all the forecasted peaks, we take the maximum of the values.

12.2.2 Methodology used for demand forecast in Poland.

Demand is influenced by a wide range of factors, making it a complex issue. On one hand, it is impacted by ambient conditions (via e.g. air conditioning, electric heating). On the other hand, some part is climate independent, and it is a structural part of demand (e.g. load of industry processes). The methodology of the Polish TSO (Polskie Sieci Elektroenergetyczne (PSE)), captures both these elements, with a strong focus on the seasonality of the demand while still incorporating the WS concept. As a result, forecasts are conducted in many different climatic conditions to enable probabilistic analysis.

In Poland, the power demand in January exceeds the May demand, even at similar ambient temperatures. This is because only a part of the demand is sensitive to temperature changes (e.g. heating, air conditioning), with the rest depending on seasonal factors (e.g. the length of the day, which affects the operation of lighting). Therefore, the first step is to develop a seasonality model by eliminating trends and normalising seasonal patterns in the data.

The next phase involves developing a thermosensitivity model as an autoregressive model, integrating temperature to reflect climate conditions. Other climate factors were omitted because they showed collinearity and were of secondary importance. The thermosensitivity model utilises the residuals from the seasonality model (values not accounted for by seasonal variations) and the temperature gradient, which is the difference between the actual temperature and the reference temperature, specifically the hourly average temperature based on all available data.

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By combining the seasonality and thermosensitivity models, we can accurately reflect demand across various ambient conditions, consistent with the PECD database.

With the use of the aforementioned models and the energy growth forecast, we project future base demand. The initial years' forecast includes changes in the demand profile, referencing historical data under uniform thermal conditions. For subsequent years, given potential trend changes and deformations, the profile is adjusted in line with the energy forecast.

Upon generating the base demand forecast, we apply dedicated temperature-dependent technological models to adjust it for trends not included in the historical data. Those models consider the evolution of specific technologies, seasonal effects, and their responsiveness to ambient temperature. The components modelled explicitly:

- EVs,
- HPs,
- data centres,
- H2 production.

The presented methodology aligns with the ENTSO-E methodology and required data formats. It offers flexibility in terms of forecast time resolution and incorporates forecasting factors such as changes in projected climate variables.

12.2.3 Methodology used for demand forecast in Belgium

The final load profiles consist of two distinct components: historical electricity consumption and the projected evolution of electricity demand. This evolution in demand is further divided into the electrification of industrial and residential loads.

Since the final load profiles are generated for future years using specific weather data, the historical load is adjusted to account for historical thermosensitivity. Therefore, the initial step involves establishing a correlation between historical electric consumption and climate conditions. Using this correlation, the historical load can then be recalibrated to match the climate conditions of the simulated year. The obtained profiles including historical thermosensitivity are then rescaled to consider the scenario-specific assumption can impact the historical load such as economic growth, energy efficiency etc.

After applying the growth factor, the electrification components are incorporated independently. These elements stem from assumptions derived from estimated market evolutions of various factors influencing electricity consumption, such as the adoption rates of HPs, EVs, and more. These assumptions are contingent upon the specific scenario and target year being simulated.

The industrial electrification encompasses projected consumption from data centres, power-to-heat technologies (e-boilers and HPs), carbon capture and storage, direct reduction iron processes using electric arc furnaces, as well as power-to-molecules technologies.

The final component involves the electrification of the residential load, encompassing EVs, HPs, air conditioning, and water heating. Each of these elements requires a calculation of hourly profiles.

For EVs, the hourly profiles are determined through a three-step process. First, the annual EVs is calculated based on the evolution of the number of EVs, assumed yearly kilometres driven and average yearly efficiency. This annual consumption is then translated into daily electricity demand using a seasonal scaling function. Finally, the daily profile is further broken down into hourly electricity demand using an intraday scaling profile, which is contingent upon the assumed system flexibility.

A similar approach is employed for HPs, air conditioning, and water heating, although the annual electricity demand is influenced by different factors such as the outside temperature.

It is important to note that batteries are not accounted for in the load profiles. Additional information can be found in the appendix of the Adequacy and Flexibility Study for Belgium 2024–2034 –published by Elia.

12.2.4 Methodology used for demand forecast in France

Drawing up load curve forecasts

Demand forecasts are prepared in two phases, as described below:

Forecasts are established for annual energy demand, for each year in the study period.

Forecasts are established for power demand on an hourly basis, using the annual energy demand forecasts calculated previously as input data.

Each phase includes a retrospective analysis of past years and an alignment with the years used as reference for simulations. It also involves a forward-looking study designed to provide a realistic idea of possible future outcomes based on today's situation and current and future trends. This includes relevant shifts that may occur based on determinants such as the electrification of space heating or the development of EVs.

Annual energy demand forecasts are calculated using an analytical approach and a stacking model. This involves dividing electricity demand into sectors of activity. The following sector breakdown has been used (starting with the highest level of demand today): residential, tertiary, industry, energy (including network losses), transport and agriculture.

Each sector is further divided into branches or end uses. Energy demand for each branch or end use is estimated by multiplying and adding together “extensive” variables (e.g. generated quantities, heated floor surface, appliances per home) and “intensive” ones (e.g. unit consumption per produced unit, per square metre, per home). The demand figures calculated in this manner are then aggregated for each sector.

To provide input data for and exploit its forecasting models, the French TSO (Réseau de Transport d’Electricité (RTE)) relies on data from research institutes (CEREN, BIPE, BatiEtude, GfK, etc.), public or semi-public institutions (INSEE, ADEME, etc.), trade associations, and other sources. The results of statistical surveys and data from RTE metering are used to align these variables with past data. Wherever possible, projections factor in information are gathered from the economic actors in question. Sector information is regularly updated to take into account new end uses, behavioural changes, and the implementation of regulations designed to improve energy efficiency.

Power demand forecasts are also calculated using a stacking method.

Each non-temperature sensitive branch or end use for which energy demand forecasts have been developed is associated with an hourly load curve profile. A significant percentage of the profiles are generated using measurements under real conditions, such as RTE metering for branches of industry connected to the transmission grid and measurement campaigns for some residential and tertiary end uses. Profiles for branches and end uses without measurements are estimated based on knowledge about the profile of the sector of activity in question.

The profiles of end-uses sensitive to weather conditions, such as heating and air conditioning, are calibrated using historical data. This calibration takes into account the seasonality of demand, building inertia, the influence of cloudiness, and the fact that the heating is only triggered when a threshold temperature is reached. The method for calibrating heat-sensitive consumption profiles pairs an iterative dichotomy process with a linear regression solved by recursive least squares. The profiles are generated based on the PECD temperature datasets.

These profiles are regularly updated to incorporate new information about the sectors and emerging end uses, as well as new technologies. Such updates require data, which RTE obtains from the measurement campaigns and surveys conducted by various players.

Based on annual energy demand for each end use or branch and the associated profiles, RTE calculates the anticipated load curve for the end use or branch for the year under review. The demand forecasts thus calculated are then aggregated to produce the load curve for France. National load curves for past years, modelled by stacking end uses or branches, are then aligned with the load curves measured for the most recent years.

12.3 Pan-European Climate database (PECDv4.2)

The PECD is at the core of ENTSO-E prospective studies. Seasonal Outlooks, ERAAs, and TYNDPs all require climatic information at high spatial[35] and temporal resolution to assess the effects of weather variability on the European power system. Other users in the energy sector also use the PECD.

To date, the different versions of the PECD have used climate reanalysis (ERA5 and ERA-interim earlier). Re-analysis can be seen as a kind of optimal interpolation of all existing observations for a long period, obtained by assimilating these observations in a climate model[36]. However, climate change should be considered when estimating the future potential of variable RES, such as wind, solar, and hydro, as well as the impact of temperature on electricity demand. This has only been partially achieved by the statistical de-trending temperature dataset in the historical reanalysis data used in previous ERAAs.

In 2022, ENTSO-E signed a memorandum of understanding (MoU) with the European Centre for Medium Range Weather Forecasts (ECMWF), which implements the EU Copernicus Climate Change Service (C3S). C3S has issued a contract led by Inside Climate Service, working with the Danish Technical University (DTU) and Mines ParisTech in which the new versions (4.x) of the PECD are developed. These new versions still include data from the past (referred to as the historical period or "historical stream") but now also include information about the future, based on projections from climate models from the CMIP6 exercise,[37] referred to as the "projection stream".

Version 4.2 of the PECD as used for the ERAA 2025 study. The full dataset – called "Climate and energy related variables from the Pan-European Climate Database derived from reanalysis and climate projections" – is available on the C3S Climate Data Store.[38] The data store contains an interface to download the dataset and a complete documentation of the solution. Exact datasets used in ERAA 2025 can be accessed on the ENTSO-E website, along with the respective study publication.

12.3.1 What does the full PECD4.2 dataset contain?

As mentioned above, PECD4.2 contains historical reanalysis data (data of the historical years), called the historical stream (HIST) and projected data for the future, called the projection stream (PROJ-):

- HIST: Contains 75 WSs,, based on 1950–2024 ERA5 reanalysis

[35] High spatial resolution is needed for wind speed and solar radiation, to accurately model the local effects for wind and solar capacity factors, even though the information is then aggregated at the PECD zone or study zone level.

[36] An explanation of historical climate reanalysis can be found on the C3S YouTube channel: https://www.youtube.com/watch?v=FAGobvUGl24&ab_channel=CopernicusECMWF

[37] The 6th Climate Model Intercomparison Project (CMIP6) is the ensemble of climate projections that constitutes the core of the scientific literature exploited in the AR6 Synthesis Report: Climate Change 2023 — IPCC of the Intergovernmental Panel on Climate Change (IPCC).

[38] C3S datastore with PECD 4.1 - https://cds.climate.copernicus.eu/datasets/sis-energy-pecd?tab=overview

- PROJ: Contains 2064 WSs based on 2015–2100 calendar years assessed under four greenhouse gas emission scenarios (shared socioeconomic pathways (SSP) scenarios) with six climate models

The SSP2-4.5 greenhouse gas emission scenario was chosen by ENSTO-E for its alignment with current emissions. This emission scenario is thereby the most probable for the coming years, considering nations' climate commitments. Nevertheless, the greenhouse gas emission scenario selection is not considered essential because the differences between the various emission scenarios are only evident from around 2035–2040, as the climate of the next 10 to 20 years will mainly be determined by the greenhouse gases already emitted in the atmosphere.

The six climate models used in PECD4.2 are AWI-CM-1-1-MR (equilibrium climate sensitivity (ECS) = 3.16 °C), BCC-ESM1 (ECS = 3.04 °C), CMCC-CM2-SR5 (ECS = 3.52 °C), EC-Earth3 (ECS = 4.30 °C), MPI-ESM1-2-HR (ECS = 2.98 °C), and MRI-ESM2-0 (ECS = 3.15 °C). These were selected by C3S and validated by ET Climate from around 20 climate models available based on the following criteria:

- The horizontal and temporal resolution of the models (the finer the better)
- The availability of simulations for all four SSP scenarios
- The structural differences among the models (to avoid choosing models that have common biases or behaviours)
- The ECS[39] of the models, which measures the diversity of the models' response to climate change, indicating the temperature increase after an equilibrium state is reached

The dataset is composed of weather and energy variables as follows (including their short names), and described in detail on the Confluence web page mentioned above:

Table 19: Time resolution for different data types

Climate data	Energy data
Hourly resolution	*Hourly resolution*
• **2m air temperature (TA)** • **Population weighted temperature (TAW)** • **Wind speed at 10 m (WS10)** • **Wind speed at 100 m (WS100)** • **Global surface solar radiation downward (GHI)**	• Wind power onshore (WON) • Wind power offshore (WOF) • Solar PV generation (SPV) • Concentrated solar power (CSP)
Daily resolution	*Daily resolution*
• **Total precipitation (TP)**	•
Weekly resolution	*Weekly resolution*
•	• Hydropower reservoirs generation energy (HRG) • Hydropower reservoirs inflow energy (HRI) • Hydropower run-of-river generation energy (HRO) • Hydropower run-of-river inflow energy (HRR) • Hydropower run-of-river with pondage generation energy (HPO)

[39] Carbon Debrief (2018): Explainer: How scientists estimate "climate sensitivity" https://www.carbonbrief.org/explainer-how-scientists-estimate-climate-sensitivity/

	• Hydropower run-of-river with pondage inflow energy (HPI) • Hydropower open-loop pumped storage inflow energy (HOL)

The energy conversion models – which allow enable the transformation of the climate information into renewable energies generation – are either physical models (wind, solar PV, and solar CSP) or statistical models (hydropower). All details of these models can be found on the Confluence web page as mentioned earlier. It should be noted that in the case of hydropower, the statistical (random forest) models need require observed data (generation and/or inflow) for the training phase. As this kind type of data is available at the country level on the Transparency Platform, the conversion models are also only at the country level.

12.3.2 What subset of PECD4.2 is used in ERAA 2025?

In ERAA 2025, 36 climate projections (referred to as WSs in the ERAA study) were chosen due to computational time and power implications. Three out of six climate models has been used (CMCC-CM2-SR5, EC-Earth3, and MPI-ESM1-2-HR) were used to maintain consistency with the in an effort to use the same WSs that were used in the previous ERAA (2024), while also and acknowledging that the remaining computational complexity of ERAA models limits the extension of WSs. The selection originated from PECD version 4.1, which was used in ERAA 2024. In that version, only three climate models were available.

From each of these three climate models 12 consecutive climate projection years were selected with the most overlap with the TYs of ERAA 2025, ensuring they would be the most representative.

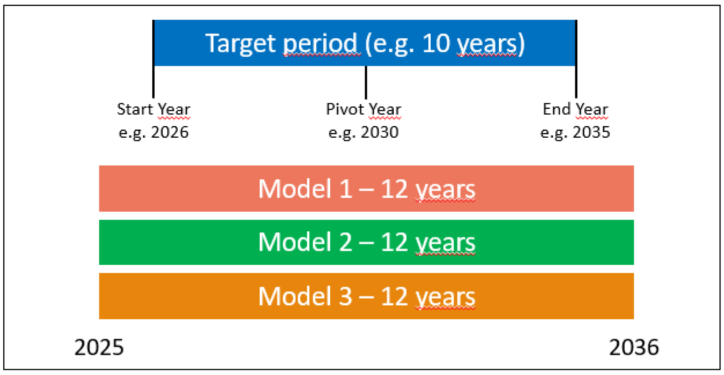

Figure 30: Climate projections in ERAA 2025

According to international standards and recommendations from the World Meteorological Organization (WMO), the **representative climate for a given year is a 30-year period surrounding the given year**. For example, to represent the climate for 2035, the period to consider would be 2021 to 2050 (or 2020 to 2049). A 20-year period can also be considered; however, in principle, no less than 20 years should be taken into account to fairly represent natural variability.

In addition, the international scientific community also strongly recommends using multiple climate models to consider the uncertainties due to each model's formulation and approximations. The 36 selected climate projection years (three climate models × 12 years each) provide a balanced compromise between model diversity and temporal coverage. This approach is therefore preferable to, for example, using six-year periods from six different climate models or a 36-year period from a single model.

Furthermore, for EVA simulations, the dataset must be reduced even further. Section 10.5 describes how a subset of 36 WSs used in ERAA 2025 was further reduced for the EVA.

Appendix 1: Detailed EVA optimisation function

The detailed formulation of the EVA optimisation model is presented in this appendix, formulated as follows:

$$Minimise \quad \sum_{y\ in\ Y} (1+r)^{(1-y)}[Total\ cost_y]$$

$$Total\ cost_y = Fixed\ cost_y + \sum_{sc\ in\ CY} \omega_{sc}[Operational\ cost_{y,sc}]$$

$$Fixed\ cost_y = \sum_{n\ in\ BZ} \left\{ \sum_{g\ in\ G_n^{new}} [(Annuity_g + FOM_{g,y}) \times p_{y,g}^c] + \sum_{g\ in\ G_n^{ex}} [FOM_{g,y} \times (P_g - p_{y,g}^d)] \right\}$$

$$Operational\ cost_{y,sc} = \sum_{n\ in\ BZ} \left[\sum_{\substack{g\ in\ G_n \\ t\ in\ T}} SRMC_{g,y} \times p_{y,sc,g,t} + \sum_{t\ in\ T} PC_{sc} \times l_{y,sc,n,t} \right]$$

$subject\ to$:

$$p_{y,sc,g,t} \le P_g - p_{y,g}^d \qquad for\ all\ y, sc, t, n\ and\ g\ in\ G_n^{ex}$$

$$p_{y,g}^d \ge p_{y-1,g}^d \qquad for\ all\ y > 1, n\ and\ g\ in\ G_n^{ex}$$

$$p_{y,sc,g,t} \le p_{y,g}^c \qquad for\ all\ y, sc, t, n\ and\ g\ in\ G_n^{new}$$

$$p_{y,g}^c \ge p_{y-1,g}^c \qquad for\ all\ y > 1, n\ and\ g\ in\ G_n^{new}$$

$$\sum\nolimits_{g\ in\ G_n^{new}} (p_{y,g}^c - p_{y,sc,g,t}) + \sum\nolimits_{g\ in\ G_n^{ex}} (P_g - p_{y,g}^d - p_{y,sc,g,t}) \ge BR_n \quad for\ all\ y, sc, t, n$$

$$\sum\nolimits_{g\ in\ G_n} p_{y,sc,g,t} + l_{y,sc,n,t} + \sum\nolimits_{i \to n} f_{y,sc,i,t} - \sum\nolimits_{i \leftarrow n} f_{y,sc,i,t} = Load_{y,sc,n,t}\ for\ all\ y, sc, n, t$$

$$f_{y,sc,i,t} \le F_{y,i,t} \qquad for\ all\ y, sc, i, t$$

where:

Sets/indices

n	Index representing study zones
CY	Set of climatic scenarios
sc	Index representing climatic scenarios
G_n	Set of all generation resources in study zone n, existing and new candidates
G_n^{ex}	Set of existing generation resources in study zone n
G_n^{new}	Set of new candidate generation resources in study zone n
Y	Set of the years in the planning horizon
y	Index representing the years of the planning horizon
g	Index representing the generators
T	Set of time steps in each year
t	Index representing the time steps
i	Index representing interconnections ($i \rightarrow n$: default direction of the interconnection is importing to study zone n, $i \leftarrow n$: default direction of the interconnection is exporting from study zone n)

Variables

$p_{y,sc,g,t}$	Generation level of unit g in year y, climatic scenario sc and time step t – [MW]
$f_{y,sc,i,t}$	Flow in interconnection i in year y, climatic scenario sc and time step t – [MW]
$p_{y,g}^c$	Capacity of the new generator g – [MW]
$p_{y,g}^d$	Capacity decommissioned from the existing unit g – [MW]
$l_{y,sc,n,t}$	Load not served in year y, climatic scenario sc, in study zone n and time step t – [MW]

Parameters

r	Discount rate [ratio]
$Annuity_g$	Annuity of the new generator g including risk premium – [€/MW]
$FOM_{g,y}$	Fixed operating and maintenance cost including risk premium – [€/MW/year]
$P_{\boldsymbol{g}}$	Capacity of the generator g – [MW]
$F_{y,i,t}$	NTC of interconnection i in year y and time step t [MW]
$SRMC_{g,y}$	Short-run Marginal cost – [€/MWh]
PC_y	Wholesale market price cap used for the year y – [€/MWh]
ω_{CY}	Probability of each climatic year scenario
BR_n	Balancing reserve requirement in study zone n – [MW]
$Load_{y,sc,n,t}$	Load level in year y, climatic scenario sc, in study zone n and time step t – [MW]

The $Fixed\ cost_y$ comprises build cost annuity (including the cost of mothballing and de-mothballing and the cost of extending the life of a unit), FOM costs for new commissioned units and FOM cost of an existing unit (or a reduced value in case the unit is mothballed).

The $Operational\ cost_{y,sc}$ comprises operation costs of producing electricity and the cost of unserved energy. In scarcity periods, the market price is assumed to reach the price cap.

Appendix 2: Mathematical Formulation of flexible EV and HP consumer (implicit DSR)

The following section presents the underlying mathematical formulation of the implicit DSR (EVs and HPs) modelling approach developed within the ERAA working group. this formulation was translated pragmatically into the modelling methodology, compatible with the characteristics and features of the market modelling tools used for the ERAA. The formulation largely follows the approach introduced in a study[40] published by APG.

The demand time series are provided in hourly granularity, and the ED problem is solved in discrete hourly time steps. The 'demand' mentioned in the rest of the chapter shall always be intended as referring to the share of price-reactive demand peculiar to HPs or EVs, respectively. We define the time index t denoting the time step δ, with $t \in \mathcal{K} \coloneqq \{1, \dots, 8760\}$.

For each δ, two decision variables are introduced, $p_i^{\mathrm{DSR}}(t)$ and $e_i^{\mathrm{DSR}}(t)$, which can be interpreted as follows:

- $p_i^{\mathrm{DSR}}(t)$: Curtailed (i.e. reduced) or increased demand of demand object i due to price-sensitive time-shifting of the demand at time step t.
- $e_i^{\mathrm{DSR}}(t)$: Amount of energy of demand object i that still must be served or has already been served at time step t.

The consumptive limitations of the flexibility resources – quantified by the respective time series – require defining the following constraint:

$$\underline{p_i}^{\mathrm{DSR}}(t) \leq p_i^{\mathrm{DSR}}(t) \leq \overline{p_i}^{\mathrm{DSR}}(t),$$

with $\overline{p_i}^{\mathrm{DSR}}(t)$ and $\underline{p_i}^{\mathrm{DSR}}(t)$ denoting the maximum demand that can be curtailed at time step t, and the maximum curtailed demand that can b²e shifted to time step t, respectively. For the amount of energy shifted to a later point in time, we define the following two constraints:

$$\underline{e_i}^{\mathrm{DSR}}(t+1) \leq e_i^{\mathrm{DSR}}(t+1) \leq \overline{e_i}^{\mathrm{DSR}}(t+1), \text{ and}$$

$$e_i^{\mathrm{DSR}}(t+1) = e_i^{\mathrm{DSR}}(t) + \delta \cdot p_i^{\mathrm{DSR}}(t).$$

[40] Haas A., Iotti G., Petz M., Misak K., Methodological developments for European Resource Adequacy Assessments, 17. Symposium Energieinnovation, 16.-18.02.2022, Graz/Austria

Here, $\overline{e_i}^{\mathrm{DSR}}(t+1)$ and $\underline{e_i}^{\mathrm{DSR}}(t+1)$ represent the maximum energy demand that can be curtailed or shifted up to time step $t+1$, respectively. Finally, as an arbitrary boundary condition, we can define:

$$e_i^{\mathrm{DSR}}(1) = e^0,$$

where the superscript 0 refers to the initial condition.

To define discrete timeframes within which the demand can be shifted (either forward or backward), the profiles $\overline{e_i}^{\mathrm{DSR}}(t+1)$ and $\underline{e_i}^{\mathrm{DSR}}(t+1)$ should be such that there exist time steps in which the two bounds coincide, i.e. there exist $h \in \mathcal{K}$ such that:

$$\overline{e_i}^{\mathrm{DSR}}(h+1) = \underline{e_i}^{\mathrm{DSR}}(h+1) = e^{\mathrm{H}}.$$

Consequently, we define the subset $\mathcal{H}$ of all these points in time as:

$$\mathcal{H} \coloneqq \left\{t \in \mathcal{K} \text{ s.t. } \overline{e_i}^{\mathrm{DSR}}(t+1) = \underline{e_i}^{\mathrm{DSR}}(t+1) = e^H \right\}.$$

Practically speaking, the elements of $\mathcal{H}$ define the boundaries of time windows within which the load can be shifted (i.e. the flexibility windows defined in the previous chapter). To ensure that all flexible demand is eventually supplied within each time window, bound by the time steps in $\mathcal{H}$, the boundary conditions are set equal to the initial condition, thus:

$$e^{\mathrm{H}} = e^0.$$

After introducing the constraints above, it is necessary to choose an appropriate set of parameters. Assuming that $\overline{p_i}^{\mathrm{DSR}}(t)$ follows the hourly demand time series of the corresponding iDSR element (e.g. HPs or EVs), it is necessary to define the remaining parameters $\underline{p_i}^{\mathrm{DSR}}(t)$, $\overline{e_i}^{\mathrm{DSR}}(t+1)$, $\underline{e_i}^{\mathrm{DSR}}(t+1)$, e^{H}, e^0 and $\mathcal{H}$.

To begin, the set $\mathcal{H}$ is defined with arbitrary time windows of six hours, whereby it follows that $\mathcal{H} \coloneqq \{6, 12, 18, 24, \dots, 8760\}$. For the sake of simplicity let $e^0 = 0$, then:

$$\overline{e_i}^{\mathrm{DSR}}(t+1) \coloneqq \begin{cases} +\infty \text{ if } t \in \mathcal{K} \setminus \mathcal{H} \\ 0 \text{ if } t \in \mathcal{H} \end{cases}, \text{and}$$

$$\underline{e_i}^{\mathrm{DSR}}(t+1) \coloneqq \begin{cases} -\infty \text{ if } t \in \mathcal{K} \setminus \mathcal{H} \\ 0 \text{ if } t \in \mathcal{H} \end{cases}.$$

To avoid negative values for $e_i^{\mathrm{DSR}}(t)$ the boundary condition $e^0 = e^{\mathrm{H}}$ can be shifted to an arbitrarily large positive number yielding the same effect (i.e. the default 50% SoC defined in the previous chapter). Finally, we can dimension $\underline{p_i}^{\mathrm{DSR}}(t)$ to allow for a maximum power absorption that matches the maximum demand curtailment in the same time window. Denoting two consecutive indices in $\mathcal{H}$ (e.g. 6 and 12) with h_i and h_{i+1}, then:

$$\underline{p_i}^{\mathrm{DSR}}(t) \coloneqq \max\left\{\overline{p_i}^{\mathrm{DSR}}(\tilde{t}) \text{ s.t. } h_i \le \tilde{t} \le h_{i+1}\right\} - \overline{p_i}^{\mathrm{DSR}}(t), \forall k \in [h_i, h_{i+1}] \subset \mathcal{K}.$$