EU-Flex Public Modelling Specification

Version 1.0

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EU-Flex Public Modelling Specification

The EU-Flex Model is a high-resolution market simulation of the European Energy system, which is built on top of the open energy system modelling framework PyPSA for which documentation is available as well.

The EU-Flex Model has been developed by ACER with the support of Open Energy Transition (OET) for the flexibility needs assessment in 2027.

Note that the documentation below contains the Public Modelling Specification for the EU-Flex Model.

26/10/2026

Version	Date	Remark
1.	26/10/2026	First public version of the Modelling Specification Document

Reference documents

- European Resource Adequacy Assessment, Annex 2: Methodology, European Network of Transmission System Operators for Electricity, 2023 Edition. Available at: https://www.entsoe.eu/outlooks/eraa/2023/report/ERAA_2023_Annex_2_Methodology.pdf.
- ACER Decision on the amendment of the determination of capacity calculation regions: Annex I, Amendment of the Determination of Capacity Calculation Regions, 19 March 2024. Available at: https://acer.europa.eu/sites/default/files/documents/Individual%20Decisions_annex/ACER_Decision_04-2024_CCR_methodology_amendment_Annex_I.pdf.
- PyPSA user guide.

Abbreviations

Acronym	Description
ACER	Agency for the Cooperation of Energy Regulators
aFRR	Automatic frequency restoration reserve
AHC	Advanced Hybrid Coupling
BZ	Bidding Zone(s)
CAPEX	Capital Expenditure
CHP	Combined Heat and Power
CNE	Critical Network Element
CNEC	Critical Network Element and Contingency
CY	Climate Year(s)
DA-UCED	Day Ahead Unit Commitment and Economic Dispatch
DSR	Demand-side Response
ED	Economic Dispatch
ENS	Energy Not Served
EMD	Electricity Market Design
ENTSO-E	European Network of Transmission System Operators for Electricity
ERAA	European Resource Adequacy Assessment
EU	European Union
EV	Electric Vehicle
EVA	Economic Viability Assessment
FBMC	Flow-based Market Coupling
FCR	Frequency Containment Reserve
FOM	Front of meter
HMMCP	Harmonised Maximum Market Clearing Price
ID-ED	Intra-Day Economic Dispatch Model

Acronym	Description
IT	Information Technology
LP	Linear Programming
mFRR	manual Frequency Restoration Reserve
MTU	Market Time Unit
NTC	Net Transfer Capacity
PECD	Pan-European Climate Database
PTDF	Power Transfer Distribution Factor
PyPSA	Python for Power System Analysis
RAM	Remaining Available Margin
RH	Rolling Horizon
RR	Replacement Reserve
TY	Target Year(s)
TYNDP	Ten-Year Network Development Plan
TSO	Transmission System Operator
VoLL	Value of lost load
VRE	Variable Renewable Energy
WACC	Weighted Average Cost of Capital

Nomenclature

Sets and Indexes

Set/Index	Description
TY	Set of target years
ty	Index for target years
CY	Set of climate years
cy	Index for climate years
OS	Set of outage scenarios
os	Index for outage scenarios
SY	Set of scenarios (Cartesian product of CY and OS)
sy	Index for scenario
RO	Set of rolling horizons
ro	Index for rolling horizon
IT	Set of EVA iterations (capacity expansion process)
it	Index for iteration
T	Set of time steps in the rolling horizon (market models DA/ID)
T'	Set of time steps retained per rolling horizon run
$T_{n,s}^{\text{must-run}}$	Set of time steps when must-run generators at bidding zone *n* must be online
T^{maint}	Set of time steps in maintenance planning horizon
$T^{\text{RH-end}}$	Set of end times of rolling horizon blocks
T_N^{ramp}	Set of N time steps with the largest absolute changes in residual load (for ramping contribution metric)
t	Index for time steps
N	Set of buses (bidding zones)
N^{CORE}	Set of buses in the CORE region (FBMC coupling)

Set/Index	Description
N^{NORDIC}	Set of buses in the NORDIC region (FBMC coupling)
n	Index for bus components (bidding zones)
L	Set of all links (CNEs, cross-border lines, AHC)
L^{FBMC}	Set of links (CNECs) using flow-based capacity allocation
L^{NTC}	Set of links using Net Transfer Capacity
L^{AHC}	Set of links using Advanced Hybrid Coupling (subset of L^{NTC})
L^{EvFB}	Set of links using evolved flow-based allocation
L^{CORE}	Set of links from CORE bidding zones to virtual CORE bus
L^{NORDIC}	Set of links from NORDIC bidding zones to virtual NORDIC bus
L^{FOR}	Set of links (interconnectors) with forced outages (subset of L)
l, l'	Indexes for link components
S^{gen}	Set of generator components
S^{UC}	Set of committable generators (subset of S^{gen})
$S^{\text{must-run}}$	Set of must-run committable generators (subset of S^{gen})
S^{VRE}	Set of variable renewable generators (subset of S^{gen})
$S^{\text{UC,fixed}}$	Set of committable generators whose commitment is fixed in ID (subset of S^{UC}); their suc/sdc are taken from DA
$S^{\text{UC,free}}$	Set of committable generators free to recommit in ID (subset of S^{UC}, configured via `id_free_commitment_carriers`); their suc/sdc are taken from ID
$S^{\text{UC},i,j}$	Set of committable generators providing service *i* in direction *j* (subset of S^{UC})
$S^{\text{gen},i,j}$	Set of generators (incl. explicit DSR) providing service *i* in direction *j* (subset of S^{gen})
S^{maint}	Set of thermal generators for maintenance planning (subset of S^{gen})
S^{maint}_{k}	Subset *k* of generators allowed in simultaneous maintenance (with $k \in SK$)
S^{store}	Set of storage components
S^{LTS}	Set of long-term storage assets (subset of S^{store})
S^{load}	Set of inelastic load components

Set/Index	Description
$S^{\text{store},i,j}$	Set of storage units (incl. implicit DSR) providing service *i* in direction *j* (subset of S^{store})
S^{exDSR}	Set of explicit DSR components (modelled as generators)
S^{imDSR}	Set of implicit DSR components (modelled as storage units)
S^{lolDSR}	Set of demand shedding DSR (loss-of-load, modelled as generators)
S^{FOR}	Set of generators and storage units with forced outages (subset of $S^{\text{gen}} \cup S^{\text{store}}$)
S^{EVA}	Set of units included in capacity expansion analysis
S^{ds}	Set of dummy storage units
S^{LoL}	Set of loss-of-load generators (load shedding)
S^{spill}	Set of load spillage generators (subset of S^{gen})
S_n^{conv}	Set of conventional generators at bidding zone *n* in the ED network of the dummy storage optimisation
S_n^{floor}	Set of conventional generators at bidding zone *n* whose technical minimum enters the dummy storage conventional floor (subset of S_n^{conv})
s	Index for generator, storage, and load components
d	Index for days
w	Index for weeks
D_d	Set of hours in day *d*
W_w	Set of days in week *w*
$W_{n,s}$	Set of implicit DSR shifting windows for component *s* at bidding zone *n*
tw	Index for time windows
I	Set of ancillary services (e.g., FCR, FRR)
i	Index for ancillary services
$J = \{+, -\}$	Set of ancillary service directions (+ for upward, - for downward)
j	Index for ancillary service directions
Q	Set of all horizon chunks across all TY/CY combinations (advanced temporal clustering, Section 3.6)
q	Index for horizon chunks

Set/Index	Description
$Q_{\text{ty,cy}}$	Set of horizon chunks belonging to target year *ty* and climate year *cy*
$\{1, \ldots, k\}$	Set of clusters, where k is the number of clusters (advanced temporal clustering, Section 3.6)
κ	Index for clusters
C_κ	Set of chunks assigned to cluster κ
q^*_κ	Medoid (centroid) chunk of cluster κ; $q^*_\kappa \in C_\kappa$
C	Set of carriers (technology groups, e.g., CCGT, wind, battery)
c	Index for carriers
S^{EVA}_c	Set of EVA assets with carrier *c* (subset of S^{EVA})
$S^{\text{EVA}}_{n,c}$	Set of EVA assets with carrier *c* at bidding zone *n* (subset of S^{EVA}; advanced temporal clustering, Section 3.6)
T_q	Set of snapshots belonging to chunk *q*

Parameters

Parameters	Description	Unit
$K_{n,l}$	incidence matrix representing if link *l* is connected to bidding zone *n* (taking values -1, 0 or 1, depending on links' connectivity and direction)	n/a
$K^{\text{AHC}}_{n,l}$	incidence matrix representing if AHC link *l* is connected to bidding zone *n* (taking value 1 if it ends in *n* and 0 otherwise)	n/a
$F^{\max}_l$	maximum capacity of link *l*	MW
$F^{\min}_l$	minimum capacity of link *l*	MW
$RAM_{l,t}$	Remaining Available Margin of FBMC link $l \in L^{\text{FBMC}}$ at time *t*	MW
$PTDF_{l,n,t}$	Power Transfer Distribution Factor of link *l* with regards to bidding zone *n* at time *t*	%
$PTDF_{l,l',t}$	Power Transfer Distribution Factor of link *l* with regards to link *l'* at time *t*	%
$\overline{g}_{n,s}$	nominal power of generator s connected to bidding zone *n*	MW

Parameters	Description	Unit
$g^{\min}_{n,s,t}$	time-dependent lower bound on the dispatch of generator *s* connected to bidding zone *n* (per unit of nominal power)	%
$g^{\max}_{n,s,t}$	time-dependent upper bound on the dispatch of generator *s* connected to bidding zone *n* (per unit of nominal power)	%
$g^{\text{must-run}}_{n,s,t}$	must-run requirement of generator *s* connected to bidding zone *n* at time *t*, derated by the unit availability $y_{n,s,t}$	MW
$g_{n,s,0}$	initial dispatch of generator *s* connected to bidding zone *n*, before the first time step of the rolling horizon of the dispatch models	MW
$T^{\text{min,up}}_{s,n}$	minimum up time of generator *s* connected to bidding zone *n*	hours
$T^{\text{min,down}}_{s,n}$	minimum down time of generator *s* connected to bidding zone *n*	hours
$suc_{n,s}$	start-up cost of generator *s* connected to bidding zone *n*	€
$sdc_{n,s}$	shut-down cost of generator *s* connected to bidding zone *n*	€
$rd_{n,s}$	ramp rate limit for decreasing the output of generator *s* connected to bidding zone *n* (per unit of nominal power)	%
$ru_{n,s}$	ramp rate limit for increasing the output of generator *s* connected to bidding zone *n* (per unit of nominal power)	%
$rdsd_{n,s}$	ramp rate limit for decreasing the output at shut-down of generator *s* connected to bidding zone *n* (per unit of nominal power)	%
$rusu_{n,s}$	ramp rate limit for increasing the output at start-up of generator *s* connected to bidding zone *n* (per unit of nominal power)	%
$MC_{n,s,t}$	marginal cost of generator/storage unit/ explicit DSR *s* connected to bidding zone *n* at time *t*	€/MWh
$soc_{n,s,0}$	initial state-of-charge of storage unit *s* connected to bidding zone *n*, before the first time step of the rolling horizon of the dispatch models	MWh
$\overline{h}_{n,s}$	nominal power of storage *s* connected to bidding zone *n*	MW

Parameters	Description	Unit
$h^{\min}_{n,s,t}$	time-dependent lower bound on the dispatch/uptake of storages connected to bidding zone *n* (per unit of nominal power)	%
$h^{\max}_{n,s,t}$	time-dependent upper bound on the dispatch/uptake of storages connected to bidding zone *n* (per unit of nominal power)	%
$nh_{n,s}$	number of hours at nominal power that fill the state-of-charge of storage *s* connected to bidding zone *n*	hours
$\eta^{\text{stand}}_{n,s}$	standing losses of storage *s* connected to bidding zone *n*	%
$\eta^{\text{store}}_{n,s}$	efficiency of storage *s* connected to bidding zone *n* when uptaking power	%
$\eta^{\text{dispatch}}_{n,s}$	efficiency of storage *s* connected to bidding zone *n* when dispatching power	%
$inflow_{n,s,t}$	inflow to the storage *s* connected to bidding zone *n* at time *t*	MW
$d_{n,s,t}$	inelastic demand (load) of load *s* at bidding zone *n* at time *t*	MW
$T_{n,s,0}$; $T_{n,s,1}$	configurable time period for explicit DSR components to keep energy conservation	hour
$R^{i,j}_{n,t}$	reserve requirements for service *i* in direction *j* by bidding zone *n* at time *t*	MW
A^{i}	full activation time of service *i*	hours
$A^{\min,i}$	minimum activation time of service *i*	hours
$pr^{i,+}_{n,s}$	maximum upward reserve provision for service *i* by generator *s* at bidding zone *n* (per unit of nominal power)	%
$pr^{i,-}_{n,s}$	maximum downward reserve provision for service *i* by generator *s* at bidding zone *n* (per unit of nominal power)	%
β^{i}	fraction of reserve *i* blocked in ID-ED	%
$soc^{\text{POtarget}}_{n,s,t}$	target state-of-charge of storage *s* connected to bidding zone *n* for the set of the rolling horizon ends $t \in T^{\text{RH-end}}$	MWh
$soc^{\text{DA/ID}}_{n,s,t}$	optimal state-of-charge of storage unit $s \in S^{\text{LTS}}$ connected to bidding zone *n* at end of rolling horizon $t \in T^{\text{RH-end}}$ (result of pre-optimisation)	MWh

Parameters	Description	Unit
$POR_{n,s}$	annual planned outage rates of generator *s* connected to bidding zone *n*	%
$DAYS_{n,s}$	total number of days per year required for maintenance of generator *s* connected to bidding zone *n*	days
$RL^{\text{peak}}_{n,t}$	peak estimated residual load of bidding zone *n* at time *t*	MW
$D^{\text{max,CY}}_{n,t}$	maximum native demand over all climate years of bidding zone *n* at time *t*	MWh
$G^{\text{min,VRE,CY}}_{n,t}$	minimum renewable generation over all climate years of bidding zone *n* at time *t*	MWh
$T^{e}_{n,s}$	earliest time maintenance of generator *s* may start	hour
$T^{l}_{n,s}$	latest time maintenance of generator *s* may start	hour
k_k	maximum units in subset *k* which are allowed in simultaneous maintenance	n/a
$t^{\text{DSR-start}}_{w}$	start time of each implicit DSR shifting window	hour
$t^{\text{DSR-end}}_{w}$	end time of each implicit DSR shifting window	hour
$D^{\text{DSR}}_{n,s,t}$	demand timeseries for implicit DSR component *s* at bidding zone *n* at time *t*	MW
$F^{\text{DSR}}_{n,s,t}$	flexible demand for implicit DSR component *s* at bidding zone *n* at time *t*	MW
$s^{\text{DSR}}_{n,s}$	non-percentage share determining the flexible portion of implicit DSR component *s* at bidding zone *n*	%
$y^{*}_{n,s,t}$	optimal maintenance plan of unit $s \in S^{\text{maint}}$ connected to bidding zone *n* at time *t* (result of pre-optimisation)	%
$ER_{n,s,t}$	exogenous revenues of generator or storage unit *s* connected to bidding zone *n* at time *t*	€
$VoLL_{n,s,t}$	value of loss-of-load of load *s* of bidding zone *n* at time *t*	€/MWh
PR_{cy}	probability of climate year *cy*	%
PR_{sy}	probability of scenario *sy*	%

Parameters	Description	Unit
$y_{n,s,t}^{\mathrm{FOR}}$	fraction of the capacity of generator/ storage unit *s* connected to bidding zone *n* that is unavailable at time *t* due to forced outage	%
$y_{l,t}^{\mathrm{FOR}}$	fraction of the capacity of interconnector *l* that is unavailable at time *t* due to forced outage	%
$cs_{\mathrm{cy,sy}}$	dummy parameter equal to 1 if *sy* uses weather year *cy*, and 0 otherwise	n/a
$NPV_{n,s}^{\mathrm{ty}}$	net present value of unit *s* connected to bidding zone *n* for target year *ty*	€/MW
$Profit_{n,s}^{\mathrm{sy,ty'}}$	profit of unit *s* connected to bidding zone *n* for year *ty'* and scenario *sy*	€/year
$Annuity_{n,s}^{\mathrm{sy,ty'}}$	annuity of unit s connected to bidding zone *n* for year *ty'* and scenario *sy*	€/year
γ	discount rate	
$IT^{\max}$	maximum number of iterations of the capacity update	n/a
$\nabla C\left(\overline{g}_{n,s,\mathrm{it}+1}\right)$	gradient of the capacity update	MW
α_0	initial learning rate for gradient descent approach	n/a
$\alpha_{\min}$; $\alpha_{\max}$	learning rate bounds for gradient descent approach	n/a
ε	convergence tolerance of capacity update	%
$\Delta g_{n,s}$	fixed step size in MW to be added to or subtracted from unit *s* connected to bidding zone *n* depending whether it is profitable (discrete-step approach)	MW
$\Delta g_{n,s}^{\mathrm{base}}$	base (starting) step size for the linear decay option	MW
$\Delta g_{n,s}^{\min}$	minimum (target) step size reached at the end of the linear decay period	MW
IT^{decay}	number of EVA iterations over which the step size is linearly decayed from $\Delta g_{n,s}^{\mathrm{base}}$ to $\Delta g_{n,s}^{\min}$	n/a
$\overline{g}_{\min,n,s}$; $\overline{g}_{\max,n,s}$	bounds of unit *s* connected to bidding zone *n* in the capacity update (discrete-step approach)	MW

Parameters	Description	Unit
C_n^{target}	curtailment reduction target for bidding zone *n*: maximum share of the available VRE energy that may be curtailed	%
$\rho_{n,s}^{\text{ds}}$	energy-power ratio of dummy storage *s* connected to bidding zone *n*	hours
$\overline{h}_{n,s}^{\text{ds}}$	nominal power capacity of dummy storage *s* connected to bidding zone *n*	MW
$c_{n,s}^{\text{ds}}$	investment cost of dummy storage *s* connected to bidding zone *n*	€/MW
$g_{n,s,t}^{\text{min,ds}}$	conventional floor of the clustered conventional generator *s* at bidding zone *n* in the dummy storage network (per unit of nominal power), built from the technical minimum of the generators in S_n^{floor} and the must-run requirement of all conventional generators, see equation (13.53)	%
c^{spill}	penalty applied to dummy storage load spillage dispatch under the capacity-minimisation objective	€/MWh
$g_{n,s,t}^{\text{ED}}$	economic dispatch result for generator/storage *s* connected to bidding zone *n* at time *t*	MW
$f_{l,t}^{\text{ED}}$	economic dispatch result for flow over link *l* at time *t*	MW
$m_{n,s,t}^{\text{ED}}$	economic dispatch result for storage charging of unit *s* connected to bidding zone *n* at time *t*	MW
$h_{n,s,t}^{\text{ED}}$	economic dispatch result for storage discharging of unit *s* connected to bidding zone *n* at time *t*	MW
$\eta_{n,s}^{\text{ch}}$	charging efficiency of storage unit *s* connected to bidding zone *n*	%
$\eta_{n,s}^{\text{dis}}$	discharging efficiency of storage unit *s* connected to bidding zone *n*	%
$\lambda_{n,s}$	self-discharge rate of storage unit *s* connected to bidding zone *n*	%
$RL_{n,t}^{\text{actual}}$	actual residual load (used in ID-ED market) at bidding zone *n* and time *t*	MWh
$RL_{n,t}^{\text{forecasted}}$	forecasted residual load (used in DA-UCED market) at bidding zone *n* and time *t*	MWh

Parameters	Description	Unit
$ct_{n,t}^{\text{base,actual}}$	actual baseline curtailment at bidding zone *n* and time *t*	MWh
$ct_{n,t}^{\text{base,forecasted}}$	forecasted baseline curtailment at bidding zone *n* and time *t*	MWh
$g_{n,s,t}^{\text{actual}}$	actual generation/load shedding at bidding zone *n* for unit *s* at time *t*	MW
$g_{n,s,t}^{\text{forecasted}}$	forecasted generation/load shedding at bidding zone *n* for unit *s* at time *t*	MW
$R_{q,n,c}$	energy revenue of carrier *c* at bidding zone *n* in chunk *q* (advanced temporal clustering, Section 3.6)	€
$\tilde{R}_{q,n,c}$	standardised revenue of BZ-carrier feature (n, c) in chunk *q*	n/a
$\mu_{n,c}$	sample mean of BZ-carrier feature (n, c) revenues across all chunks	€
$\sigma_{n,c}$	sample standard deviation of BZ-carrier feature (n, c) revenues across all chunks	€
w_κ	weight of cluster κ; fraction of total chunks across all CYs that cluster κ represents; sums to 1.0 globally	n/a
k	number of clusters (configurable via `n_clusters`)	n/a
H	number of horizon chunks per climate year	n/a
$freq$	full-run frequency; full market simulation is triggered every $freq$ iterations (configurable via `full_run_frequency`)	n/a

Variables

Variable	Description	Unit
$f_{l,t}$	flow over link *l* at time *t*	MW
$np_{n,t}$	net position of bidding zone *n* at time *t*	MW
$\lambda_{n,t}$	zonal price at bidding zone *n* in time *t*	€/MWh

Variable	Description	Unit
$g_{n,s,t}$	dispatch of generator/explicit DSR/loss-of-load generator *s* connected to bidding zone *n* at time *t*	MW
$u_{n,s,t}$	commitment binary variable of generator s connected to bidding zone *n* at time *t*. It is equal to 1 if the generator is online, and 0 if it is offline. Included for committable generators in the set S^{UC}	n/a
$suc_{n,s,t}$	start-up cost of generator s connected to bidding zone *n* at time *t*	€
$sdc_{n,s,t}$	shut-down cost of generator *s* connected to bidding zone *n* at time *t*	€
$h_{n,s,t}$	dispatch of storage unit *s* connected to bidding zone *n* at time *t*	MW
$m_{n,s,t}$	uptake of storage unit *s* connected to bidding zone *n* at time *t*	MW
$spillage_{n,s,t}$	spillage of the storage s connected to bidding zone *n* at time *t*	MW
$soc_{n,s,t}$	state-of-charge of storage unit *s* connected to bidding zone *n* at time *t*	MWh
$r^{i,j}_{n,s,t}$	reserved amount of service *i* in direction *j* of generator/storage unit *s* in bidding zone *n* at time *t*	MWh
$\lambda^{i,j}_{n,t}$	opportunity cost of reserve *i* in direction *j* in bidding zone *n* at time *t*	€/MWh
$cm_{n,t}$	net capacity margin at time *t* for each bidding zone *n*	MW
$y_{n,s,t}$	binary maintenance status of generator *s* at time *t* (1 = in maintenance, 0 = available)	n/a
$x_{n,s,t}$	binary variable representing if maintenance of generator *s* connected to bidding zone *n* starts at time *t*	n/a
α_{it}	learning rate of gradient descent approach at iteration *it*	n/a

Metrics

Metric	Description	Unit
$RL_{n,t}$	residual load at time *t* at bidding zone *n*	MW
$RL_{\text{daily},n,d}$	daily flexibility need of bidding zone *n* for day *d* (sum of absolute hourly deviations from daily mean)	MWh
$RL_{\text{weekly},n,w}$	weekly flexibility need of bidding zone *n* for week *w* (hourly sum of absolute deviations of the daily mean from the weekly mean)	MWh
$RL_{\text{seasonal},n,\text{ty}}$	seasonal flexibility need of bidding zone *n* (hourly sum of absolute deviations of the monthly mean from the annual mean)	MWh
$RM_{n}^{\max}$	maximum ramping requirement bidding zone *n* must handle	MW
$CB_{\text{daily},n,s}$	daily contribution of generator, storage, or demand response resource *s* to flexibility needs of bidding zone *n* (using dispatch variations)	MWh
$CB_{\text{weekly},n,s}$	weekly contribution of generator, storage, or demand response resource *s* to flexibility needs of bidding zone *n* (using dispatch variations)	MWh
$CB_{\text{seasonal},n,s}$	seasonal contribution of generator, storage, or demand response resource *s* to flexibility needs of bidding zone *n* (using dispatch variations)	MWh
$CB_{\text{daily},n,l}$	daily contribution of interconnector *l* to flexibility needs of bidding zone *n* (using flow variations)	MWh
$CB_{\text{weekly},n,l}$	weekly contribution of interconnector *l* to flexibility needs of bidding zone *n* (using flow variations)	MWh
$CB_{\text{seasonal},n,l}$	seasonal contribution of interconnector *l* to flexibility needs of bidding zone *n* (using flow variations)	MWh
CT_{n}^{base}	total baseline curtailment at bidding *n* zone over all time steps	MW
CT_{n}^{adj}	total adjusted curtailment at bidding *n* zone over all time steps	MW

Metric	Description	Unit
VRE_n^{req}	minimum required storage capacity to eliminate curtailment at bidding zone *n*	MW
$FE_{n,t}$	forecast errors in renewable generation and load	MW
RM_t^{needed}	ramping shortfall at time *t*	MW
$ENS_{n,\text{sy}}$	Energy Not Served in scenario *sy* in bidding zone *n*	MW
$\overline{rl}_{n,d}$	daily average residual load at bidding zone *n* for day *d*	MW
$\overline{rl}_{n,w}$	weekly average residual load at bidding zone *n* for week *w*	MW
$\overline{rl}_{n,\text{mo}}$	monthly average residual load at bidding zone *n* for month *mo*	MW
$\overline{rl}_{n,\text{ty}}$	annual average residual load at bidding zone *n* for year *ty*	MW
$\overline{g}_{n,s,d}$	daily average dispatch of asset *s* at bidding zone *n* for day *d*	MW
$\overline{g}_{n,s,w}$	weekly average dispatch of asset *s* at bidding zone *n* for week *w*	MW
$\overline{g}_{n,s,\text{mo}}$	monthly average dispatch of asset *s* at bidding zone *n* for month *mo*	MW
$\overline{g}_{n,s,\text{ty}}$	annual average dispatch of asset *s* at bidding zone *n* for year *ty*	MW
$\overline{f}_{l,d}$	daily average flow on interconnector *l* for day *d*	MW
$\overline{f}_{l,w}$	weekly average flow on interconnector *l* for week *w*	MW
$\overline{f}_{l,\text{mo}}$	monthly average flow on interconnector *l* for month *mo*	MW
$\overline{f}_{l,\text{ty}}$	annual average flow on interconnector *l* for year *ty*	MW
RM_t	absolute ramp in residual load at time *t*	MW
$RM_t^{\text{available}}$	total available ramping capability from dispatchable generation, storage discharge, and demand-side response at time *t*	MW

Metric	Description	Unit
$RC_{n,s}$	contribution fraction of technology *s* to ramping needs in bidding zone *n* during extreme ramping events	n/a
$FE_{n}^{\mathrm{tot,up/down}}$	total upward/downward forecast error energy at bidding zone *n*	MWh
FE_{n}^{q}	*q*-th percentile of the signed forecast error at bidding zone *n*, per climate year	MW
$FE_{n}^{q,\mathrm{pool}}$	*q*-th percentile of the signed forecast error at bidding zone *n*, pooled across all climate years	MW
$FE_{n,t}^{\mathrm{curt}}$	short-term curtailment shortfall at bidding zone *n* and time *t*	MWh
$FE_{n}^{\mathrm{curt,tot}}$	total short-term curtailment shortfall over the entire year at bidding zone *n*	MWh
$FE_{n}^{\mathrm{curt,max}}$	maximum short-term curtailment shortfall at bidding zone *n*	MWh
$FE_{n,t}^{\mathrm{ens}}$	short-term energy not served (ENS) shortfall at bidding zone *n* and time *t*	MWh
$FE_{n}^{\mathrm{ens,tot}}$	total short-term ENS shortfall over the entire year at bidding zone *n*	MWh
$FE_{n}^{\mathrm{ens,max}}$	maximum short-term ENS shortfall at bidding zone *n*	MWh
$FE_{n,s}^{\mathrm{cont}}$	contribution of technology *s* to managing forecast errors at bidding zone *n* (using dispatch variations)	MWh
$FE_{n,l}^{\mathrm{cont}}$	contribution of interconnector *l* to managing forecast errors at bidding zone *n* (using flow variations)	MWh
$\overline{\Delta g}_{n,s}$	annual mean of the dispatch change between actual and forecasted for asset *s* at bidding zone *n*	MW
$\overline{\Delta f}_{l}$	annual mean of the flow change between actual and forecasted for interconnector *l*	MW
$ct_{n,t}^{\mathrm{base}}$	baseline curtailment at bidding zone *n* and time *t*	MWh

1. Context

1.1. Project background

The recently adopted Regulation (EU) 2024/1747 of the European Parliament and Council, dated 13 June 2024, amends Regulation (EU) 2019/942 to improve the Union's electricity market design (EMD) reforms. These reforms place an obligation on the European Union Agency for the Cooperation of Energy Regulators (ACER) to conduct an EU-wide assessment of flexibility needs in the electricity sector.

To fulfil this obligation, ACER has developed the EU-Flex model with the support of Open Energy Transition (OET).

The EU-Flex model is built in Python for Power System Analysis (PyPSA), an open source toolbox for simulating and optimising modern power and energy systems. PyPSA includes essential features such as conventional generators with unit commitment, variable wind and solar generation, storage units, coupling to other energy sectors, and mixed alternating and direct current networks. PyPSA is designed to scale well with large networks and long time series, making it an ideal tool for studying flexibility in the context of the EU's energy transition.

Building on these capabilities, the project team has developed a comprehensive EU energy network model using PyPSA. This model serves as the analytical backbone of the EU-Flex assessment, enabling ACER to quantify flexibility requirements across different scenarios of VRE integration, evaluate potential system constraints, and identify optimal pathways for maintaining grid stability while advancing the EU's clean energy objectives.

1.2. Scope

The EU-Flex model's design, development, and validation process is detailed in this document in order to provide stakeholders with a comprehensive overview of the implementation approach. It defines the technical framework, specifies input requirements, outlines analysis methodologies, and describes expected outputs.

Each feature of the EU-Flex model is described in numbered subsections in the following way. The **Background** subsection outlines the context and rationale for the feature, with particular focus on its role in flexibility assessment. The **Target** subsection defines the specific capabilities and objectives of the feature. The **Implementation Strategy** subsection details the approach to meet these objectives, covering foundational principles, required inputs and outputs, mathematical formulation, and framework integration.

2. Technical foundation

2.1. Core components

The model has six core components shown in **Figure 1**. The first is **Input Data / Pre-processing**, which represents the various repositories (public or custom) used to provide input data for the model. The next five components form the high-level workflow, defining the sequential processes that drive the model's operation.

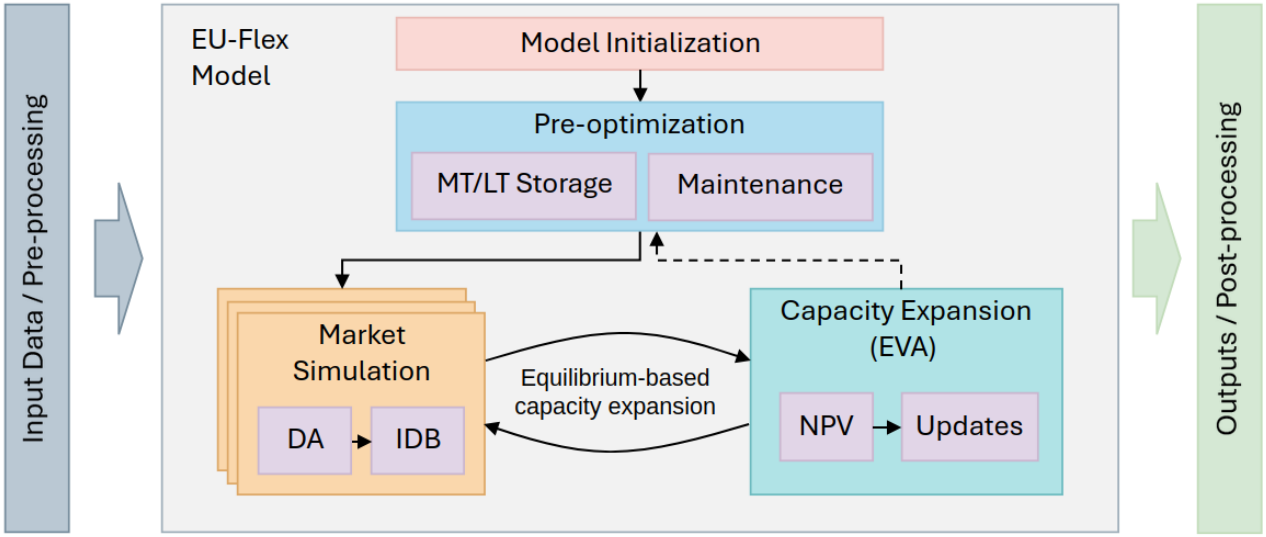


Figure 1: High level overview of the model.

- **Input Data / Pre-processing:** Storage of all datasets required to run the EU-Flex model. Includes pre-processing features to prepare the data for the model, such as converting raw data into a format suitable for analysis, aggregating data from multiple sources, and ensuring consistency across datasets.

- **Model initialisation:** Imports the grid topology, demand information, and initial generation and storage assets along with their operational and economic characteristics to model readable format.

- **Pre-optimisation:** Evaluates the target storage levels for medium and long-term storage facilities (block MT/LT Storage), i.e. the state of charge that hydro reservoirs and pumped storage should have at the boundaries of each rolling horizon of the market models (Section 3.2.1), using a coarse-resolution year ahead Economic Dispatch (ED) model with perfect foresight. Determines the optimal maintenance schedule of thermal generators consistent with the ENTSO-E maintenance planning methodology (block Maintenance). It should be noted that, as captured by the dashed arrows in **Figure 1** from capacity update to pre-optimisation and

market simulation, the EU-Flex model can be configured by the user to re-optimise storage and/or maintenance plans after a certain number of capacity update iterations. This approach is further discussed in sections Model initialisation and Pre-optimisation.

- **Market Simulation:** Generates multiple sample datasets (scenarios) based on historical weather patterns and stochastic outages of generation capacity through Monte-Carlo sampling. A day-ahead Unit Commitment and Economic Dispatch (DA-UCED) optimisation is performed to determine which power plants are committed, and are therefore available for dispatch in the intraday market. The DA-UCED results define the set of available generators for the intra-day and balancing Economic Dispatch (ID-ED) optimisation, which incorporates actual demand and production data. The DA-UCED and ID-ED model produce day-ahead and intra-day and balancing electricity prices and quantities.

- **Capacity Expansion:** Assess the financial viability of adding or removing capacity for selected components using the NPV per MW metric, which is in turn obtained from the revenues and costs computed through the DA-UCED and ID-ED models. Market simulations are performed iteratively over sampled scenarios until the Economic Viability Assessment (EVA) has converged, or until a maximum number of iterations is reached. The EVA has converged when, in every target year, the NPV per MW of every asset lies within a configurable tolerance around zero; see Section 3.4.3.

- **Outputs / Post-processing:** Extract results and perform detailed analysis. This includes technological and regional contributions to meeting flexibility needs as well as negative externalities allocated to missing flexibility in the system including curtailment, load shedding, or reserve shortages. Additionally, economic and market insights are derived to understand price formation and system costs. Scenario comparisons and sensitivity analyses help assess system performance under uncertainty, while visualisations and reports provide clear, data-driven insights for decision-making.

A detailed flow chart of the calculation methodology is provided in the Appendix (Section Detailed flow chart).

2.2. System configuration

Table 1 shows the list of parameters that are configurable in the model to the user. They are further detailed in their respective sections, along with a discussion on how they may impact trade-offs on computational complexity and accuracy for the EU-Flex model.

Table 1: List of configurable parameters.

Parameter	Proposed Default	Affected component(s)
Load scaling factor	1.0	Input Data / Pre-processing

Parameter	Proposed Default	Affected component(s)
Capacity scaling factor of generators and storage units	1.0	Input Data / Pre-processing
Minimum capacity of generators and storage units	0.001 MW	Input Data / Pre-processing
Enable renewable negative pricing	false	Input Data / Pre-processing
Per-carrier renewable negative pricing configuration	not set	Input Data / Pre-processing
Set of target years	2026, 2028, 2030, 2035	Input Data / Pre-processing
Include DSR	true	Input Data / Pre-processing
Include explicit DSR	true	Input Data / Pre-processing
Include implicit DSR	true	Input Data / Pre-processing
Initial SOC percentage for implicit DSR	50%	Input Data / Pre-processing
Forecast timeseries source	noise (synthetic)	Input Data / Pre-processing
Forecast error noise multiplier	1.0	Input Data / Pre-processing
DA renewable timeseries multiplier	1.0	Input Data / Pre-processing
DA load timeseries multiplier	1.0	Input Data / Pre-processing
ID renewable timeseries multiplier	1.0	Input Data / Pre-processing
ID load timeseries multiplier	1.0	Input Data / Pre-processing
Temporal resolution of pre-optimisation	8h	Pre-optimisation
Enable maintenance planning	true	Pre-optimisation
Maintenance plan source	`optimize` (SA-based)	Pre-optimisation
Maintenance plan ID (when source is plan-id)	not set	Pre-optimisation
Maximum SA iterations for maintenance planning	5000	Pre-optimisation
Number of parallel SA runs per CPU core	1	Pre-optimisation
Enable forced outages	true	Monte Carlo sampling
Sample size of forced outage scenarios	1	Monte Carlo sampling
Random seed for forced outages	18	Monte Carlo sampling
Set of climate years	1982 (WS1) to 2017 (WS36)	Monte Carlo sampling

Parameter	Proposed Default	Affected component(s)
Length of rolling horizon	72h (3 days)	Market models (DA-UCED and ID-ED)
Overlap of rolling horizon	24h (1 day)	Market models (DA-UCED and ID-ED)
Market interconnection method	physical (NTC)	Market models (DA-UCED and ID-ED)
Unit commitment formulation	`linearized-simple`	Market model (DA-UCED)
Reserves option	co-optimised	Market model (DA-UCED)
Reserve directions	both	Market model (DA-UCED)
Enable reserve shedding generators	false	Market models (DA-UCED and ID-ED)
FCR capacity blocked in intraday	1.0 (100%)	Market model (ID-ED)
FRR capacity blocked in intraday	0.0 (0%)	Market model (ID-ED)
FRR blocking method in intraday	imbalance	Market model (ID-ED)
Explicit DSR DA-to-ID dispatch fixed fraction	0.0	Market model (ID-ED)
Implicit DSR DA-to-ID dispatch fixed fraction	0.0	Market model (ID-ED)
LP status residuals patching tolerance	1e-4	Market models (DA-UCED and ID-ED)
Ramp adjustment tolerance for ID patching	1e-4	Market model (ID-ED)
Enable storage technical/historical constraints	true	Market models (DA-UCED and ID-ED)
Perfect foresight mode	false	Market models (alternative mode)
Price cap update	true	Capacity expansion
Starting price cap for day-ahead	5000, 5000, 5000, 5000 €/MWh	Capacity expansion
Starting price cap for intraday and balancing	10000, 10000, 10000, 10000 €/MWh	Capacity expansion
Price cap increment when event happens	500 €/MWh	Capacity expansion
Maximum price cap	20000 €/MWh	Capacity expansion
Multi-year method of price cap	expected	Capacity expansion
Use technology-specific hurdle rates	true	Capacity expansion
Discount rate (fallback)	5%	Capacity expansion
Climate year weights for NPV	not set (equal weights)	Capacity expansion

Parameter	Proposed Default	Affected component(s)
Convergence tolerance of capacity update	70000 €/MW	Capacity expansion
Maximum number of iterations of the EVA	3	Capacity expansion
Size of capacity added or removed	800 MW	Capacity expansion
Enable linear step decay	true	Capacity expansion
Target minimum step size	10 MW	Capacity expansion
Number of decay iterations	same as maximum iterations	Capacity expansion
Enable exogenous revenue streams	false	Capacity expansion
Enable mothballing	true	Capacity expansion
Enable lifetime extension	true	Capacity expansion
Dummy storage optimisation	true	Post-processing & model outputs
Dummy storage share across countries	true	Post-processing & model outputs
Dummy storage minimise total cost	true	Post-processing & model outputs
Dummy storage energy to power ratios	1, 2, 4, 6, 12, 24, 48, 168	Post-processing & model outputs
Dummy storage curtailment targets	0.05 (5%)	Post-processing & model outputs
Dummy storage per-bidding-zone curtailment targets	false (uses config values)	Post-processing & model outputs
Dummy storage network needs (TSO/DSO)	false	Post-processing & model outputs
Dummy storage enable load spillage	true	Post-processing & model outputs
Short-term flexibility requirements method	simulation	Post-processing & model outputs
NECP RES generation target comparison	not set (disabled)	Post-processing & model outputs
CO2 emissions target comparison	not set (disabled)	Post-processing & model outputs
Shadow prices extraction	not set (disabled)	Post-processing & model outputs
Enable horizon clustering	false	Advanced temporal clustering
Number of K-medoids clusters	12	Advanced temporal clustering
Full run frequency (iterations)	10	Advanced temporal clustering
Clustering horizon chunk length (days)	7	Advanced temporal clustering
Clustering random seed	42	Advanced temporal clustering

3. Modelling framework specification

Each component in this section is described in three parts: **Background** gives the context and motivation, **Target** states what the component must achieve, and **Implementation strategy** describes how it is implemented in the EU-Flex model. The main configurable parameters and their default values are listed in Table 1 (Section System configuration).

3.1. Model initialisation

This section outlines the initialisation of all components necessary for executing the workflow calculation steps, from pre-optimisation to post-processing. It defines nine key components that serve as the foundation of the proposed models: Geographical coverage, Target years, Climate years, Temporal granularity, Network graph and transmission, Generation resources, Energy storage, Demand and demand-side response, and Ancillary services and reserves management.

While many parameters can be adjusted through input variations, the configurable parameters are specifically aligned with those defined in Section System configuration. The components described here form the basis for model construction, solving, and analysis in Sections Pre-optimisation through Post-processing. The final results of these components emerge in later sections, where the models are executed.

3.1.1. Geographical coverage

3.1.1.1. Background

The European electricity market is divided into distinct bidding zones, captured by **Figure 2** below, which are set to manage network congestion and facilitate efficient market operation. These zones traditionally align with national borders, though some countries like Norway, Sweden, and Italy are divided into multiple zones to better reflect internal network constraints. The evolving nature of the European power system, particularly with increasing renewable integration, requires a flexible approach to geographical modelling. The geographical coverage ensures that all significant power system interactions and flexibility resources across the European continent are captured in the assessment.

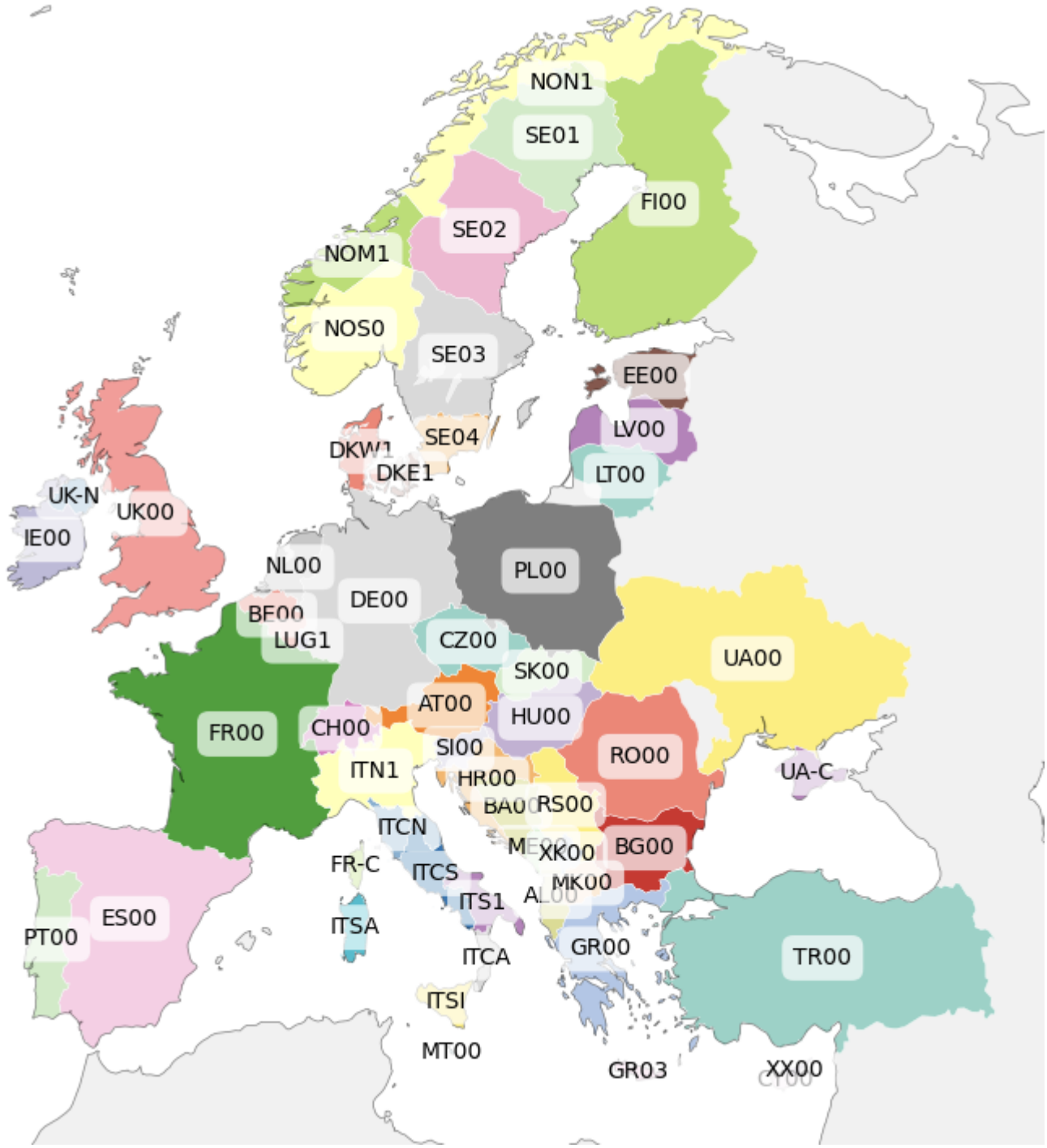


Figure 2: Bidding zones incorporated in the assessment. Zone codes follow the ERAA convention: the two-letter country code followed by two characters identifying the zone within the country, where “00” denotes a country that forms a single bidding zone (e.g. FR00).

3.1.1.2. Target

The modelling framework explicitly considers all EU Member States and strategically important neighbours: Nordic countries, United Kingdom, Moldova, Ukraine, Albania, Bosnia and Herzegovina, Kosovo[1], Montenegro, North Macedonia, and Serbia. The explicitly modelled bidding zones are given in **Figure 2**. Beyond these, the system accounts for peripheral countries through exogenous

boundary conditions. If, e.g., as a result of the current or future bidding zone review, bidding zone configurations change, users can easily adapt the model bidding zones.

3.1.1.3. Implementation strategy

The modelling framework uses the bidding zones as defined by ACER. The bidding zone configurations are defined by a complete set of “shape files” which define the geographical boundaries of each zone. The system architecture provides the flexibility to interchange these input files by an updated configuration of bidding zones as currently under review to accommodate future changes in market structure and bidding zone configurations. The bidding zone shape files can be retrieved from the ENTSO-E Transparency Platform or related sources[2].

Each bidding zone is modelled as a copper plate, assuming perfect internal transmission without constraints. The only exception is the current German-Luxembourg bidding zone, which is the only one spanning across multiple countries. For this particular case, the bidding zone is represented by two regions with an infinitely large interconnection. This setup provides the flexibility to set country specific boundary conditions for Germany and Luxembourg while keeping the regions copper-plated in one market.

In the network graph representation the implementation translates to one node per bidding zone, except for the mentioned German-Luxembourg case. At this representative node all associated power system components are attached, representing the market participants for the bidding zone. The modelling framework allows the assignment of power system components to the bidding zones through direct allocation or geographical mapping.

Peripheral countries are modelled as external zones connected to the main network through fixed exchange links. This allows representing cross-border flows with neighbouring non-modelled regions (e.g., Ukraine, Morocco, Balearic Islands). The exchanges with the periphery are treated as exogenous inputs, defined through time series of power injections or withdrawals at the respective bidding zone borders. An additional virtual generator is added to each peripheral country bidding zone to enforce the balancing of these zones.

The bidding zones defined here, with their attached power system components, are used in the definition of the Network graph in Section Network graph and transmission.

3.1.2. Target years

3.1.2.1. Background

The need for a multi-year assessment horizon stems from the EMD reforms, which place an obligation on ACER to evaluate medium to long-term flexibility needs. This forward-looking approach is essential for identifying potential system challenges and enabling timely infrastructure development and policy responses.

3.1.2.2. Target

The temporal evaluation scope covers a forward-looking period of 5 to 10 years from the publication date, with the first EU-wide flexibility needs assessment capable of modelling every target year between 2028 and 2037. These years serve as reference points for evaluating both infrastructure development and policy implementation timelines. The user can select a set of Target Years (TYs) in the workflow configuration to be calculated.

3.1.2.3. Implementation strategy

The model implements a flexible approach (via a configurable parameter) to handle future scenarios through a target year setting mechanism. When configured, the network model incorporates the possibility to:

1. Define renewable availability time series
2. Define demand time series
3. Adjust interconnector capacities
4. Align with country-specific renewable expansion trajectories aligned with national energy and climate plans
5. Adjust for scheduled decommissioning of conventional power plants in accordance with national phase-out policies

All input data for a given target year, such as demand time series or policy-driven capacity constraints can be configured by ACER. In the workflow configuration files, the user has the ability to select the set of target years as long as data is available for the selected target years.

3.1.3. Climate years

3.1.3.1. Background

The integration of renewable energy sources introduces weather-dependent variability into power systems. Historical weather patterns significantly influence renewable generation profiles and demand patterns as well as long-term storage planning. Consequently, in order to capture this variability and ensure a robust flexibility assessment, multiple climate years (CYs) must be considered in the analysis.

3.1.3.2. Target

The model supports the analysis of multiple CYs, allowing users to select specific historical weather years. This multi-year approach ensures that the flexibility assessment accounts for

various weather conditions and their impact on both generation and demand patterns. The set of CYs is used for the Monte-Carlo sampling defined in Section Monte Carlo Sampling.

3.1.3.3. Implementation strategy

All weather-dependent input data for different CYs, such as wind and solar generation profiles, hydro inflows, and temperature-dependent demand variations, are provided by ACER. Users can specify which CYs to include in the analysis through the workflow configuration files.

3.1.4. Temporal granularity

3.1.4.1. Background

To effectively assess flexibility requirements, the model's temporal resolution should be fine enough to capture the constraints imposed by flexible power plants and variations in dispatchable demand. However, this need for high resolution must be balanced against computational limitations to ensure results are generated within a reasonable timeframe, allowing for robust analysis. An hourly representation of time dependent data balances these considerations.

3.1.4.2. Target

The model operates with an hourly time step resolution for all modelled years.

3.1.4.3. Implementation strategy

The PyPSA framework inherently supports temporal resolution analysis to arbitrary intervals. Thus, a configurable temporal resolution comes naturally with the use of the software. However, the practical implementation depends significantly on input data availability. When working with mixed-resolution input data, time series can be resampled through interpolation or other appropriate techniques, if needed. The computational and storage resources required for these adjustments scale with both the temporal resolution and the complexity of the input dataset. This creates a trade-off between temporal granularity and computational efficiency that must be carefully balanced based on the specific assessment objectives. The temporal resolution of the model determines the Market Time Unit (MTU).

3.1.5. Network graph and transmission

3.1.5.1. Background

As outlined in Section Geographical Coverage, the European electricity market is divided into bidding zones to manage transmission-level network congestion both between and within zones while facilitating market operations. Market coupling is crucial in Europe as it enables the efficient allocation of electricity across borders, ensuring that the lowest-cost generation resources are utilised first. It also leads to the enhancement of system flexibility through the enabling of cross-border balancing and reserve sharing, helping manage fluctuations in supply and demand. Moreover, this interconnected system is continuously evolving, requiring a flexible approach to network representation. Therefore, representing the European electricity market as an implementable network is essential for performing calculations while maintaining a dynamic, adaptable structure that ensures both realism and practical implementability.

Moreover, a key challenge in coupling the different European bidding zones is cross-border capacity allocation, as electricity flows according to physical grid constraints rather than direct commercial paths between generators and consumers. While cross-zonal capacities aid in grid flexibility by enabling electricity to flow between zones, particularly during unbalanced supply and demand conditions, this also creates a mismatch between commercial and physical flows, requiring careful transmission capacity management [3].

To address these complexities, the European coupled market relies on two primary models: Net Transfer Capacity (NTC) and Flow-Based Market Coupling (FBMC). In the NTC approach, cross-border trades for a given MTU do not influence exchange capacities on other borders during market clearing. In contrast, FBMC accounts for interdependencies between bidding zones and cross-border capacities, providing a more accurate representation of the interconnected grid's physical constraints[4]. Both models must be integrated into market operations and formulations to ensure realistic cross-border exchange limits in economic models. Additionally, Advanced Hybrid Coupling (AHC) is considered for bidding zones that lie between NTC and FBMC regions.

3.1.5.2. Target

The modelling framework offers a comprehensive representation of the European electricity market, incorporating the bidding zones shown in **Figure 2** along with the connected peripheral countries. Designed for adaptability, it can seamlessly integrate updates to reflect evolving structural and regulatory changes.

More specifically, the framework includes a network representation that accurately captures the European geographical coverage, bidding zones, and the coupling models (NTC and FBMC) used between them. For each bidding-zone border, the models offer the flexibility to choose between these two methods for capacity allocation. Moreover, the network model remains flexible, ensuring it can accommodate future modifications in market structures, grid configurations, and capacity allocation methodologies.

3.1.5.3. Implementation strategy

The **Network** component of PyPSA is used to model the European electricity market's transmission system. This component functions as a graph-based structure that organises and manages various network elements.

Within this structure, the **Bus** component serves as the fundamental node to which all loads, generators, storage units, lines, transformers, and links are connected. Its primary role is to enforce energy conservation for all attached elements, and in the model, it is used to represent bidding zones.

The **Link** component is responsible for modelling controllable, directed power flows between two buses. This versatile element can represent various transmission components, including bidirectional HVDC links, unidirectional lossy HVDC connections, AC/DC converters, and other interconnections. In the European electricity network model, Links are used to represent transmission elements such as Critical Network Elements and Contingencies (CNECs)[5] and cross-border lines. These links include capacity constraints, which are used to define NTCs or Remaining Available Margins (RAMs), depending on the applicable capacity allocation model (NTC or FBMC). Advanced hybrid coupling (AHC) is used to model links between bidding zones applying NTC and bidding zones applying FBMC models. Additionally, where relevant, Power Transfer Distribution Factors (PTDFs) are incorporated to accurately reflect the impact of power flows across the grid. The capacity allocation model is selected with the configurable parameter "Market interconnection method", as described in the note at the end of this section; with FBMC, the treatment of each link then follows automatically from the regions of the bidding zones it connects.

When FBMC is selected, two virtual bidding zones are added to model the flow-based constraints, one for the CORE region and one for the NORDIC region. They have no generators, storage units, or loads. The links between the bidding zones in the CORE region and in the NORDIC region are removed and replaced by links between the bidding zone and the virtual node representing its region (in sets L^{CORE} and L^{NORDIC}). Their flows can be interpreted as a net export from (import to) these bidding zones to (from) the region, and are unlimited. The equations below are applied to these virtual bidding zones and links.

Mathematically, the net position of bidding zones is defined as:

$$np_{n,t} = \sum_{s} g_{n,s,t} + \sum_{s} h_{n,s,t} - \sum_{s} m_{n,s,t} - \sum_{s} d_{n,s,t} \quad \forall t \in T, \forall n \in N \tag{1.1}$$

In equation (1.1), the net position of bidding zone *n* at time *t* is calculated as the sum of the total power generation ($g_{n,s,t}$) plus the total storage dispatch ($h_{n,s,t}$) minus the total storage uptake ($m_{n,s,t}$) minus the total load ($d_{n,s,t}$). The net position represents the total amount of electricity to be exported from or imported by bidding zone *n*. Note that the net position of virtual bidding zones CORE and NORDIC is 0.

Using the net positions, enforcing bidding zone's energy conservation is integrated into the modelling framework via equation:

$$np_{n,t} - \sum_{l} K_{n,l} f_{l,t} = 0 : (\lambda_{n,t}) \quad \forall t \in T, \forall n \in N \tag{1.2}$$

More specifically, equation (1.2) represents the energy balance per bidding zone. It ensures that the net position at every bidding zone equals the total imports ($K_{n,l} f_{l,t}$ with $K_{n,l} = -1$) minus the total exports ($K_{n,l} f_{l,t}$ with $K_{n,l} = 1$). $\lambda_{n,t}$ is the equation's dual variable, which represents the clearing price of the bidding zone *n* at time *t*.

Moreover, the cross-zonal capacity allocation methods are integrated into the modelling framework via the equations below, as detailed for ERAA 2024 in the FB readme[6]:

$$F_l^{\min} \leq f_{l,t} \leq F_l^{\max} \quad \forall t \in T, \forall l \in L^{\text{NTC}} \cup L^{\text{EvFB}} \tag{1.3}$$

$$\sum_{l' \in L^{\text{AHC}} \cup L^{\text{EvFB}} \cup L^{\text{CORE}} \cup L^{\text{NORDIC}}} PTDF_{l,l',t} f_{l',t} \leq RAM_l \quad \forall t \in T, \forall l \in L^{\text{FBMC}} \tag{1.4}$$

$$np_{\text{CORE},t} = 0, np_{\text{NORDIC},t} = 0 \quad \forall t \in T \tag{1.5}$$

Equations (1.3) and (1.4) prevent links' overloading in the market models, depending on the allocation model used for the link. In equation (1.3), the flow over the network link ($f_{l,t}$) is limited by its cross-zonal capacity ($F_l^{\min}$ and $F_l^{\max}$; transmission within a bidding zone is not modelled) for those modelled with NTC or the evolved flow-based approach. AHC links may both consider NTCs and CNECs for different components of this formulation, determined based on specific network characteristics. Equation (1.4) calculates the flow over FBMC links (the CNECs in the set L^{FBMC}) using the PTDF matrices of the links to virtual CORE/NORDIC buses, of the flows coming from AHC zones ($l' \in L^{\text{AHC}}$), and of the flows on evolved flow-based links ($l' \in L^{\text{EvFB}}$). Finally, equation (1.5) defines that the net position of the Core and Nordic region should be zero. We note that the flows induced by evolved flow-based (EvFB) are assumed to be decoupled from other study zones' net position. As such, they are not accounted for in equation (1.2), following the FB ERAA methodology[6]. Decoupled virtual buses and links are added to the network to represent the evolved-flow based links in order to limit their flows.

As outlined in the 2023 ERAA methodology[7], NTC values are provided by transmission system operators (TSOs) as hourly forecasts, aggregated per border by combining TSOs' data for different connection types (e.g., HVDC and HVAC). Planned transmission line maintenance is integrated into the hourly NTC availability, reducing capacity accordingly. Additionally, both planned and unplanned outages must be considered in the TSOs' NTC calculations.

The flow-based domains for links in L^{FBMC} define the solution space for the net positions of individual bidding zones for a given MTU. They are derived by analysing active power flows across monitored network elements—referred to as Critical Network Elements (CNEs)—and assessing how changes in the net positions impact these elements. To ensure grid security, relevant contingencies are considered, representing N-1 security constraints. This results in a list of Critical Network Elements and Contingencies (CNECs), where each CNE is paired with specific

contingencies under which it is monitored. For each CNEC, a RAM is defined, limiting power flow and ultimately constraining the net positions of bidding zones within the flow-based domains. Additionally, PTDFs are computed to quantify the impact of net position changes on the CNECs. The full methodology for selecting CNECs, calculating PTDFs, and determining RAMs is detailed in the 2023 ERAA methodology.

In both capacity allocation models, the modelling framework can leverage the latest ERAA study data, including NTCs, AHCs, CNECs, EvFB, PTDFs, and RAMs.

> Note: The configurable parameter "Market interconnection method" selects one capacity allocation model for the whole network:
>
> - **NTC** (default; options `ntc` and `physical`, which give the same market model): the original cross-border links are kept and no virtual buses are added. The flows over all links, including those inside the CORE and NORDIC regions, are limited by their NTC values through equation (1.3), and equations (1.4) and (1.5) are not included in the model.
>
> - **FBMC** (option `fbmc`): the network is adapted as described above. Links inside the CORE and NORDIC regions are replaced by links to the virtual CORE and NORDIC bidding zones and constrained by the flow-based domains through equations (1.4) and (1.5); links between these regions and the other bidding zones are modelled with AHC; and links between bidding zones outside both regions, as well as evolved flow-based links, remain limited through equation (1.3). This option requires the ERAA flow-based data, so it is only available for climate years for which flow-based domains are provided.

Finally, periphery countries are added to the network as external zones connected to the main network through fixed exchange links. These links have unlimited capacity, and their flows are defined through time series of power injections or withdrawals at the respective bidding zone borders, i.e. $f_{l,t} = FIXED_{l,t}$ for link l connecting the periphery country to the main network.

3.1.6. Generation resources

3.1.6.1. Background

In the current European energy landscape, market participants supply energy from a mix of dispatchable and non-dispatchable sources. Dispatchable power plants, such as thermal, hydropower, and gas-fired plants, can be controlled to adjust their output based on market and grid conditions. In contrast, non-dispatchable sources, like solar and wind, depend on resource availability and cannot be adjusted on demand. Some dispatchable generators, such as combined cycle gas turbines, can provide flexibility to the grid by adjusting their output to meet varying demands.

In this model, dispatchability is influenced not only by the availability of power but also by how certain technologies, such as nuclear power, interact with the market. For instance, nuclear plants typically operate under base load conditions and may have operational constraints that limit their flexibility in responding to market signals.

PyPSA provides a catalogue of predefined components that represent key elements of the energy system. Generators and Storage Unit components are configured to dispatch and store power according to their technological and market characteristics. This section outlines the specific requirements and configurations for technologies modelled using the generator component, ensuring that each resource behaves appropriately within the simulation.

3.1.6.2. Target

The model should account for both non-dispatchable and dispatchable resources. Non-dispatchable generation is constrained by the availability of solar and wind resources, while dispatchable sources are categorised as either flexible or inflexible, with some plants also contributing to combined heat and power production (CHP). For inflexible units (coal, nuclear and biomass), the model considers constraints such as minimum generation levels, ramp rates, minimum up/down times, and the startup time required for the plant to become operational. Run-of-river hydropower plants are modelled as generators, however reservoir and pumped storage hydropower plants are modelled as storage units.

3.1.6.3. Implementation strategy

The Generator component in PyPSA is used to model all generators except hydropower plants. Each generator is connected to a single bus, converting energy from its designated carrier to the carrier of the attached bus. Appropriate constraints should be applied to each generator to ensure accurate representation. Where feasible, generators should be aggregated in a way that preserves key operational characteristics influencing grid flexibility requirements while avoiding distortions in the modelling outcomes. A configuration option (Unit-level representation) is available to load unit-level data or ERAA aggregated data.

The generator constraints are integrated in the modelling framework via the equations below:

$$g^{\min}_{n,s,t}\overline{g}_{n,s} \leq g_{n,s,t} \leq g^{\max}_{n,s,t}\overline{g}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{gen}} \setminus S^{\text{UC}} \tag{2.1}$$

$$g^{\min}_{n,s,t}\overline{g}_{n,s}u_{n,s,t} \leq g_{n,s,t} \leq g^{\max}_{n,s,t}\overline{g}_{n,s}u_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{UC}} \tag{2.2}$$

$$\sum_{t'=t}^{t+T^{\min,\text{up}}_{s,n}} u_{n,s,t'} \geq T^{\min,\text{up}}_{s,n}\left(u_{n,s,t} - u_{n,s,t-1}\right) \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{UC}} \tag{2.3}$$

$$\sum_{t'=t}^{t+T^{\min,\text{down}}_{s,n}} (1 - u_{n,s,t'}) \geq T^{\min,\text{down}}_{s,n}\left(u_{n,s,t-1} - u_{n,s,t}\right) \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{UC}} \tag{2.4}$$

$$suc_{n,s,t} \geq suc_{n,s}\left(u_{n,s,t} - u_{n,s,t-1}\right) \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{UC}} \tag{2.5}$$

$$sdc_{n,s,t} \geq sdc_{n,s}\left(u_{n,s,t-1} - u_{n,s,t}\right) \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{UC}} \tag{2.6}$$

$$-rd_{n,s}\overline{g}_{n,s} \leq g_{n,s,t} - g_{n,s,t-1} \leq ru_{n,s}\overline{g}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{gen}} \setminus S^{\mathrm{UC}} \tag{2.7}$$

$$\begin{aligned}\left[-rd_{n,s}u_{n,s,t} - rdsd_{n,s}\left(u_{n,s,t-1} - u_{n,s,t}\right)\right]\overline{g}_{n,s} &\leq g_{n,s,t} - g_{n,s,t-1} \\ &\leq \left[ru_{n,s}u_{n,s,t-1} + rusu_{n,s}\left(u_{n,s,t} - u_{n,s,t-1}\right)\right]\overline{g}_{n,s} \\ &\quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{UC}}\end{aligned} \tag{2.8}$$

$$g_{n,s,t}^{\mathrm{must-run}} \leq g_{n,s,t} \quad \forall n \in N, \forall s \in S^{\mathrm{must-run}} \tag{2.9}$$

The constraint in equation (2.1) limits the dispatch variable $g_{n,s,t}$ of non-committable generators (i.e., generators in the set $S^{\mathrm{gen}} \setminus S^{\mathrm{UC}}$) to their minimum and maximum allowable outputs. Notice that $g_{n,s,t}^{\min}$ and $g_{n,s,t}^{\max}$ are time-dependent extra lower and upper restrictions on the dispatch (expressed as a fraction of the nominal power), e.g., in case of wind reduced availability, a power plant de-rating, or a minimum stable output restriction. If no restrictions exist, $g_{n,s,t}^{\min} = 0$ and $g_{n,s,t}^{\max} = 1$. In the case of run-of-river generators, the $g_{n,s,t}^{\max}$ is determined by the inflows into the generator. Similarly, equation (2.2) limits the dispatch of committable generators (i.e., generators in the set S^{UC}), taking into account if the generator is online ($u_{n,s,t} = 1$) or offline ($u_{n,s,t} = 0$).

For committable generators, additional constraints are included to restrict their operation. Equation (2.3) enforces a minimum amount of time slots that the generator must run consecutively $T_{s,n}^{\mathrm{min,up}}$ before it shuts-down. Similarly, equation (2.4) enforces a minimum amount of time slots that the generator must remain offline ($T_{s,n}^{\mathrm{min,down}}$) before it starts-up. Equations (2.5) and (2.6) define, respectively, the start-up and shut-down costs to be included in the objective function, which are incurred when the generator transitions from OFF to ON and vice-versa.

Ramp rate constraints are defined by equations (2.7) and (2.8), for, respectively, non-committable and committable generators. They limit the rate at which a generator can change its output between time steps. Note that $g_{n,s,0}$ is considered when evaluating these equations in the first time step of *T*.

Equation (2.9) enforces must-run generators (in the set $S^{\mathrm{must-run}}$) must be always producing above their must-run capacity $g_{n,s,t}^{\mathrm{must-run}}$ level for all time steps t, although adjusted for the unit availability $y_{n,s,t}$ from either planned or forced outages to avoid infeasibilities.

For bidding zones representing peripheral countries, a virtual generator is added to each zone to ensure balance, given that fixed positive or negative flows enter or leave these areas. This virtual generator has unlimited capacity and can be dispatched in both directions (representing either generation or load), i.e., $g^{\min} * n, s, t = -1$ and $g^{\max} * n, s, t = 1$. Its marginal cost is set to zero so that it does not influence prices of study zones.

The constraints relevant to each technology modelled as a Generator component is given in **Table 2**. The table excludes the nominal power ($\overline{g}_{n,s}$) as that is a requirement for all technologies. Costs of CO2 are embedded in the marginal cost of the generators, taking account of the efficiency $\eta_{n,s}$ of generator *s* at bidding zone *n* and specific emission factors of the power plants. This is deemed a better representation of market dynamics as CO2 costs are included by generators in their

market bids. The ($g^{\max}_{n,s,t}$) variable is included for all generator components to capture the both planned and unplanned maintenance, as further discussed in Section Pre-optimisation.

Table 2: Components modelled as Generators in PyPSA.

Technology	$g^{\min}_{n,s,t}$	$\frac{ru}{d_{n,s}}$	$T^{\min}_{\text{up/down}}$	$MC_{n,s,t}$	$g^{\max}_{n,s,t}$	$\eta_{n,s}$	S^{UC}	CO_2
Coal	✓	✓	✓	✓	✓	✓	TRUE	Yes
Nuclear	✓	✓	✓	✓	✓		TRUE	No
Biomass	✓	✓	✓	✓	✓	✓	TRUE	No
Solar				✓	✓		FALSE	No
Wind				✓	✓		FALSE	No
CCGT	✓	✓	✓	✓	✓	✓	TRUE	Yes
OCGT	✓	✓	✓	✓	✓	✓	FALSE	Yes
Run-of-river				✓	✓		FALSE	No
Oil	✓	✓	✓	✓	✓	✓	TRUE	Yes
Lignite	✓	✓	✓	✓	✓	✓	TRUE	Yes
Biofuel	✓	✓	✓	✓	✓	✓	TRUE	Yes
Geothermal				✓	✓		FALSE	No
Other non-renewables[9]	✓	✓	✓	✓	✓	✓	TRUE	Yes
Other renewables[10]				✓	✓		FALSE	No

Note: The configurable parameter “Capacity scaling factor of generators and storage units” is used to scale the capacity of the generators $\overline{g}_{n,s}$ in an automated way (for scenario generation and debugging). Moreover, the configurable parameter “Minimum capacity of generators and storage units” is used to set the minimum capacity $\overline{g}_{n,s}$ of the units participating in the EVA to a small value (e.g., 0.001 MW) so they can have a positive/negative NPV during the capacity update step.

To model subsidy-driven bidding behaviour where some renewable capacity bids below zero to ensure dispatch, the model implements a negative pricing feature. When enabled, renewable generators are split into two components:

1. **Original generator**: Retains $(1 - \sigma_s)$ of the original capacity with the original marginal cost
2. **_NEG generator**: A new generator with σ_s of the original capacity bidding at a negative marginal cost MC^{neg}_s

The capacity split is defined by:

$$\overline{g}_{n,s}^{\text{orig}} = (1 - \sigma_s) \cdot \overline{g}_{n,s} \tag{2.10}$$

$$\overline{g}_{n,s}^{\text{neg}} = \sigma_s \cdot \overline{g}_{n,s} \tag{2.11}$$

where:

- $\overline{g}_{n,s}$ is the original nominal capacity of generator s at bus n
- $\sigma_s \in [0, 1]$ is the share of capacity allocated to negative pricing (configurable per carrier)
- $MC_s^{\text{neg}} < 0$ is the negative marginal cost in EUR/MWh

The _NEG generator inherits:

- The same bus connection as the original generator
- The same carrier type
- The same availability profile ($g_{n,s,t}^{\max}$)

This feature applies to configurable renewable carriers (default: Solar (PV), Wind Onshore, Wind Offshore, Hydro - Run of River (Turbine)).

> Note: Negative pricing is configurable via configuration parameter `eva.base_network.negative_pricing`.

3.1.7. Energy Storage

3.1.7.1. Background

Energy storage technologies are increasingly being integrated in the EU electricity markets due to the storage systems' ability to enhance the efficiency, reliability, and flexibility of the grid. Storage systems help balance the variability of renewable energy sources and provide flexibility to the grid by storing excess energy during periods of high renewable energy generation and discharging the stored electricity during periods of low generation (or periods of high demand). The discharge of storage energy during periods of high demand (peak load) can also help reduce the need for expensive and less efficient peaking power plants. Additionally, storage systems can act as reserves and quickly provide power when needed (reserves are discussed in detail in Section Ancillary services and reserves management).

There are a number of challenges with integrating and modelling storage systems in electricity markets – stemming from the unique operational characteristics of storage systems and the complexities of accurately modelling storage behaviour. In the cases of hydropower systems, there is the added complexity of accounting for reservoirs and related water/environmental constraints.

Furthermore, because storage systems can both charge and discharge, they require unique participation within electricity markets from traditional generators, for example.

3.1.7.2. Target

The modelling platform incorporates storage systems, namely batteries, hydro reservoirs, and pumped hydropower. The PyPSA components used to represent storage and hydropower characterise the operations of these storage systems, including the state of charge, the associated efficiency of a charging-discharging cycle, and standing losses. In addition to those parameters, in the case of hydropower, the tool considers constraints related to energy availability, such as associated reservoir size or environmental constraints that impose minimum energy release requirements.

3.1.7.3. Implementation strategy

Storage systems are modelled within PyPSA as **Storage Units**. Each storage unit is attached to a single bus and is used for intertemporal power shifting. Additionally, each storage unit has a time-varying state of charge and specified efficiencies for charging and discharging. Storage units are optimised for economic dispatch and scheduling and are modelled with the ability to charge and discharge electricity into the markets. Batteries are modelled as dispatchable resources, with constraints on charging/discharging efficiencies, state of charge, and standing losses. In the particular case of hydropower units, the reservoir is represented as an equivalent MWh unit, where water stored corresponds to potential energy. Hydropower reservoirs receive inflow from runoff and have the ability to spill water in terms of energy excess. They do support active charging and only have the ability to discharge electricity. Pumped hydropower units receive no inflow and are able to actively charge energy.

Mathematically, the storage constraints are integrated in the modelling framework via the equations below:

$$h^{\min}_{n,s,t}\overline{h}_{n,s} \leq h_{n,s,t} \leq h^{\max}_{n,s,t}\overline{h}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store}} \tag{3.1}$$

$$h^{\min}_{n,s,t}\overline{h}_{n,s} \leq m_{n,s,t} \leq h^{\max}_{n,s,t}\overline{h}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store}} \tag{3.2}$$

$$m_{n,s,t} \geq m^{\min}_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store}} \tag{3.3}$$

$$0 \leq soc_{n,s,t} \leq nh_{n,s}\overline{h}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store}} \tag{3.4}$$

$$\begin{aligned} soc_{n,s,t} = {} & \eta^{\text{stand}}_{n,s} soc_{n,s,t-1} + \eta^{\text{store}}_{n,s} m_{n,s,t} \\ & - \frac{1}{\eta^{\text{dispatch}}_{n,s}} h_{n,s,t} + inflow_{n,s,t} - spillage_{n,s,t} \end{aligned} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store}} \tag{3.5}$$

In Equations (3.1) and (3.2), both the dispatch ($h_{n,s,t}$) and uptake ($m_{n,s,t}$) variables are constrained by the storage nominal power ($\overline{h}_{n,s}$) scaled by time series of minimum ($h^{\min}_{n,s,t}$) and maximum ($h^{\max}_{n,s,t}$) values. These time series must be expressed as per-unit values of nominal power, strictly within the range (0,1). Incorporating these bounds allows for the representation of various real-world

constraints, such as minimum energy release requirements due to reservoir storage limitations in hydropower systems or environmental restrictions on water discharge. In Equations (3.3) the minimum pumping power constraints are enforced.

In (3.4), the state-of-charge of the storage unit ($soc_{n,s,t}$) is limited to its energy capacity (calculated by maximum number of hours $nh_{n,s}$ times the nominal power).

In (3.5), the state-of-charge dynamics is represented as a function of: the state-of-charge in the previous time slot times the storing losses ($\eta_{n,s}^{\text{stand}}$)[11] plus the uptaking times the efficiency $\eta_{n,s}^{\text{store}}$ minus the dispatching divided by the efficiency $\eta_{n,s}^{\text{dispatch}}$ plus the inflow ($inflow_{n,s,t}$), minus the spillage ($spillage_{n,s,t}$). The inclusion of inflow time series and spillage variables depends on the type of storage unit. For example, hydro reservoirs include these parameters, whereas pumped hydro systems do not include them and their inflow values are set to 0. Additionally, in the cases of hydro reservoirs, $\eta_{\text{store};n,s}$ is set at 0 to disallow pumping/active charging – these units only discharge electricity. Another input into the dispatch model is the initial state of charge of storage systems ($soc_{n,s,0}$), which is used to evaluate equation (3.5) when considering the first time slot of the rolling horizon *T*. For hydropower units, the water resource potential is converted into an equivalent MWh that is used as $soc_{n,s,0}$.

The constraints relevant to each storage technology modelled as a Storage Unit component are given in **Table 3**. The check marks define which parameters are defined. The special cases for the inflow into pumped storage plants and uptaking power for reservoir based hydropower plants are given a value of 0.

Table 3: Storage and hydropower systems modelled in PyPSA.

name	$\overline{h}_{n,s}$	$nh_{n,s}$	$h_{n,s,t}$	$m_{n,s,t}$	$spillage_{n,s,t}$	$inflow_{n,s,t}$	$\eta_{n,s}^{\text{store}}$	$soc_{n,s,0}$
Battery	✓	✓	✓	✓			✓	✓
Hydro - Reservoir	✓	✓	✓		✓	✓		✓
Hydro - Pump Storage Closed Loop (Pumping)	✓	✓	✓	✓			✓	✓
Hydro - Pump Storage Open Loop (Pumping)	✓	✓	✓	✓			✓	✓
Hydro - Pondage	✓	✓	✓		✓	✓		✓

Note: The configurable parameter “Capacity scaling factor of generators and storage units” is used to scale the capacity of the storage units $\overline{h}_{n,s}$ in an automated way (for

scenario generation and debugging). Moreover, the configurable parameter "Minimum capacity of generators and storage units" is used to set the minimum capacity $\overline{h}_{n,s}$ of the units participating in the EVA to a small value (e.g., 0.001 MW) so they can have a positive/negative NPV during the capacity update step. Finally, the configurable parameter "Unit-level representation" is available to load unit-level data or ERAA aggregated data.

3.1.8. Demand and demand-side response

3.1.8.1. Background

Demand plays a fundamental role in electricity markets, driving system dispatch needs and influencing overall costs. Consumers span various sectors—industrial, commercial, and residential—each with distinct consumption patterns, operational constraints, and responsiveness to price signals. These differences shape market dynamics and impact how flexibility can be leveraged to balance supply and demand efficiently.

One of the key mechanisms for enhancing system flexibility is demand-side response (DSR). Demand assets, regardless of their connection level (industrial, commercial, or residential), exhibit inherent elasticities and can adjust their consumption based on market conditions.

DSR can be classified into implicit and explicit approaches. Implicit DSR occurs when consumers modify their electricity usage in response to price variations, contributing to demand shaving or shifting without actively participating in the market. This typically happens through time-of-use tariffs, critical peak pricing, or real-time price adjustments that encourage users to adapt their consumption behaviour.

In contrast, explicit DSR involves direct market participation, where consumers—or aggregators acting on their behalf—offer flexibility as a service. This is achieved through mechanisms such as price-responsive bidding curves, demand reduction commitments, or participation in ancillary services markets. Explicit DSR enables demand assets to function similarly to generation assets, providing markets and system operators with additional tools for grid balancing, congestion management, and peak load reduction.

As the European electricity markets evolve and integrate more variable renewable energy sources, the role of DSR becomes increasingly critical in ensuring system stability, enhancing market efficiency, and reducing reliance on conventional generation for flexibility.

3.1.8.2. Target

The modelling framework represents the inelastic demand of bidding zones as a time series with a temporal resolution defined in Section Temporal granularity, which is linked to each CY as defined in Section Climate years. To enhance granularity, multiple demand time series can be

assigned to each bidding zone, allowing the total demand to be segmented by sector (e.g., industrial, commercial, residential) and/or consumer type (e.g., electric vehicles—EVs).

Additionally, the framework integrates elastic demand by modelling both implicit and explicit DSR in both directions: upward (demand reduction) and downward (demand increase). DSR providers can offer various services, such as peak shaving, load shedding, and load shifting, to enhance system flexibility.

The scope of DSR technologies extends beyond traditional demand response mechanisms and includes emerging flexible loads, such as electric vehicles (e.g., smart charging and vehicle-to-grid), heat pumps, smart home energy management systems, and electrolysers.

Implicit DSR is represented through typical user consumption profiles, enabling demand shifts within predefined time windows, while explicit DSR is activated on a market basis, with a maximum capacity pre-defined. The model also supports the definition of diverse use cases with specific characteristics, such as commercial EV fleets or residential EV owners leveraging smart home charging solutions.

3.1.8.3. Implementation strategy

The **Load** component in PyPSA is used to model the inelastic demand of each bidding zone. It is assigned to a specific Bus, allowing demand to be linked to the corresponding bidding zone. An active power consumption time series represents demand variations over the target period. By default, the Load component assumes positive values when consuming active power from the bus.

Mathematically, the inelastic demand of the bidding zones is considered in equations already described in this document, such as the bidding zone net position calculation in equation (1.1).

Implicit DSR is modelled using the storage component described in Section Energy storage, allowing a portion of demand to become responsive to market conditions at each time step and enabling demand shifting. In this representation, equation (3.5) excludes time series for inflow and spillage variables, as they are not relevant for DSR, while efficiency parameters reflect consumer elasticities or cycle efficiency.

The storage nominal power ($\overline{h}_{n,s}$) in equations (3.1)-(3.4) defines the maximum and minimum demand flexibility at each time step, representing the extent to which demand can be increased or reduced (in terms of power and energy).

For some implicit DSR technologies, such as out-of-market batteries, the storage nominal capacity is defined by the installed capacity in the bidding zone times the share of demand that is flexible. The storage capacity is calculated similarly. The initial state-of-charge ($soc_{n,s,0}$) is set to a configurable percentage of the storage energy capacity, reflecting the typical starting point of demand flexibility (typically 50%). The cyclic efficiency is also given and defines the dispatch efficiency of the implicit DSR component.

For other technologies such as electric vehicles (EVs) and heat pumps (HPs), to capture their varying availability—for example, fleets of electric vehicles may only be available for responding during specific periods (e.g., daytime or nighttime)—time series for the minimum and maximum demand flexibility can be set by means of the parameters $h^{\min}_{n,s,t}$ and $h^{\max}_{n,s,t}$.

To ensure that total demand remains unchanged over the implicit DSR shifting windows, the storage level is constrained to maintain overall energy balance over each configurable period, enforcing

$$soc_{n,s,t_w^{\mathrm{DSR-start}}} = soc_{n,s,t_w^{\mathrm{DSR-end}}} = SOC^{\mathrm{DSR}}_{n,s} \cdot \overline{h}_{n,s} \quad \forall w \in W_{n,s} \tag{4.1}$$

Where $W_{n,s}$ is the set of windows for that technology in the bidding zone, $t_w^{\mathrm{DSR-start}}$ is the start time of the shifting window w, and $t_w^{\mathrm{DSR-end}}$ is the end time of the shifting time window w. Outside of the shifting windows, the state-of-charge is set to stay as $SOC^{\mathrm{DSR}}_{n,s}$, so the storage unit cannot charge or discharge. The minimum and maximum charging/discharging are also enforced as below. Note that $SOC^{\mathrm{DSR}}_{n,s}$ is a configurable parameter ("Initial SOC percentage for implicit DSR") that can be set to 0, 50%, or 100% of the storage energy capacity.

The implicit DSR components are linked to a demand timeseries $D^{\mathrm{DSR}}_{n,s,t}$ and a non-percentage share $s^{\mathrm{DSR}}_{n,s}$ to determine its portion that is flexible. The flexible demand at each timestep is defined as:

$$F^{\mathrm{DSR}}_{n,s,t} = D^{\mathrm{DSR}}_{n,s,t} \cdot s^{\mathrm{DSR}}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{imDSR}}$$

This flexible demand represents the actual portion of demand that can be shifted at each timestep. These parameters define time-varying charging/discharging limits as follows:

For each time window $w \in W_{n,s}$, the maximum discharge limit (demand reduction) is calculated as the flexible demand available at each timestep:

$$h^{\max}_{n,s,t} = \frac{F^{\mathrm{DSR}}_{n,s,t}}{\overline{h}_{n,s}} \quad \forall w \in W_{n,s}, \forall t \in T[t_w^{\mathrm{DSR-start}}, t_w^{\mathrm{DSR-end}}], \forall n \in N, \forall s \in S^{\mathrm{imDSR}} \tag{4.2}$$

The minimum dispatch limit (maximum demand increase) is defined as the negative of the available headroom, representing how much additional demand can be added at each timestep without exceeding the window's maximum flexibility capacity:

$$h^{\min}_{n,s,t} = -\left(\frac{\max_{[t_w^{\mathrm{DSR-start}}, t_w^{\mathrm{DSR-end}}]} F^{\mathrm{DSR}}_{n,s,t}}{\overline{h}_{n,s}} - \frac{F^{\mathrm{DSR}}_{n,s,t}}{\overline{h}_{n,s}}\right) \tag{4.3}$$
$$\forall w \in W_{n,s}, \forall t \in T[t_w^{\mathrm{DSR-start}}, t_w^{\mathrm{DSR-end}}], \forall n \in N, \forall s \in S^{\mathrm{imDSR}}$$

Note that for time slots outside of the shifting windows, both $h^{\max}_{n,s,t} = 0$ and $h^{\min}_{n,s,t} = 0$.

As defined in equations (3.1) and (3.2), both the dispatch ($h_{n,s,t}$, representing demand reduction) and uptake ($m_{n,s,t}$, representing demand increase) variables are constrained by the storage nominal power ($\overline{h}_{n,s}$) scaled by these time-varying minimum ($h^{\min}_{n,s,t}$) and maximum ($h^{\max}_{n,s,t}$) values. Since implicit DSR represents load flexibility, positive dispatch reduces demand while negative

dispatch (charging) increases demand. Both constraints are now time-varying based on the actual flexible demand at each timestep, allowing more realistic modelling of DSR availability. Figure 3 illustrates how the implicit DSR component operates within a defined shifting window and based on a flexible demand timeseries.

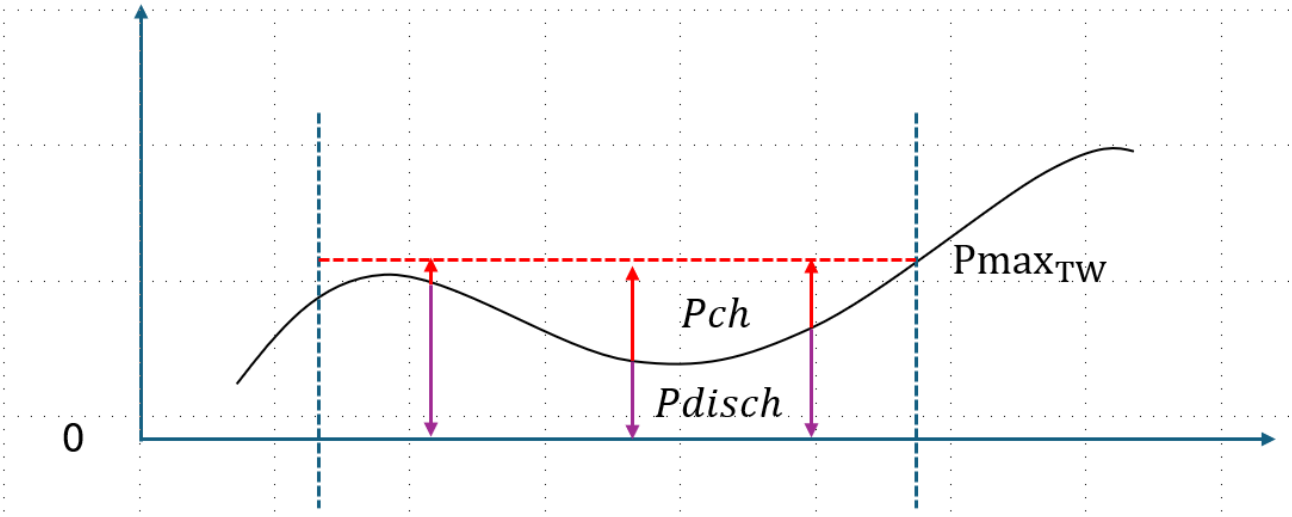


Figure 3: Example of implicit DSR operation within a shifting window.

The set S^{imDSR} represents all implicit DSR components modelled as storage units, allowing for a structured yet flexible approach to demand flexibility representation.

Explicit DSR is modelled by the **Generator** component described in Section Generation resources. Some features are modified from Generator's default configuration to allow it to represent an explicit DSR:

- A set of explicit DSR components modelled as generators is defined as S^{exDSR}.
- To allow both power production and consumption, the time-dependent lower bound on the dispatch of generator ($g^{\min}_{n,s,t}$) can be set to negative values, enabling the generator to take both positive and negative values, with dispatch determined by its marginal cost.
- If the available power for DSR varies over time, the $g^{\min}_{n,s,t}$ and $g^{\max}_{n,s,t}$ time series assume varying values to adjust the component's flexibility.
- If the explicit DSR is of type load shifting, a constraint is applied to ensure that the net sum of all power produced and consumed over a configurable period ($T_{n,s,1} - T_{n,s,0}$) remains zero, which is defined as follows:

$$\sum_{t=T_{n,s,0}}^{T_{n,s,1}} g_{n,s,t} = 0 \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{exDSR}} \tag{4.4}$$

- Equation (4.4) is not included in case the explicit DSR is of type load shedding (e.g., used for peak shaving).

- The nominal power of the DSR generator ($\overline{g}_{n,s}$) is defined as the maximum load that the component can shift/shed.
- A marginal cost function is added to the DSR generator to represent the demand responsiveness to the market (i.e., the activation prices requested by the explicit DSR asset).
- The component retains full access to all standard features in the Generator component.
- If the explicit DSR can be activated for at most a number of hours H per day, the representing generator is considered committable (but without ramping, maximum up, maximum down limits) and the following constraint is added to the model:

$$\sum_{t \in D} u_{n,s,t} \leq H \quad \forall D, \forall n \in N, \forall s \in S^{\text{exDSR}} \tag{4.5}$$

Where D is the set of days in the rolling horizon length.

A loss-of-load (LoL) demand shedding DSR is also modelled in the bidding zones (set S^{lolDSR}). Again, the **Generator** component is used, which is added to each bidding zone to represent the cost of not fulling the demand. In this case, $g^{\min}_{n,s,t}$ is set to -1, and $g^{\max}_{n,s,t}$ is set to 0 in order to capture a negative dispatch. The nominal power of this demand shedding generator ($\overline{g}_{n,s}$) is set as the maximum demand shedding, and its dispatch cost is calculated as the market price cap - representing the maximum cost of not fulfilling the demand, thus the value of lost load (VoLL).

> Note: Some configurable parameters are available to configure the Demand and DSR components. “Load scaling factor” is available to scale the demand (up or down) in an automated way. “Include DSR” is used to define if DSR components should be included (or not) in the market models. Same logic for configurable parameters “Include explicit DSR” and “Include implicit DSR”.

3.1.9. Ancillary services and reserves management

3.1.9.1. Background

System operators rely on reserve products such as Frequency Containment Reserves (FCR) and Frequency Restoration Reserves (FRR) to procure the flexibility needed to maintain grid stability and respond to fluctuations in the network. FRR includes automatic FRR (aFRR) and manual FRR (mFRR), which are aggregated together in the EU-Flex model. As the share of renewable energy sources increases, balancing supply and demand becomes increasingly complex, making it essential for system operators to accurately estimate and procure reserve requirements. In this context, modelling reserves is crucial for assessing the long-term flexibility needs of the European power system and ensuring that future market designs support a resilient and reliable energy transition.

An effective reserve modelling approach ensures that these services are procured efficiently, striking a balance between system security and cost-effectiveness. Since reserve providers must withhold capacity from the energy market, they incur opportunity costs, making it essential for the model to capture this trade-off and ensure fair compensation. Different generation and storage technologies have unique technical capabilities, so reserve allocation must be optimised to maximise efficiency. Additionally, considering cross-border reserve procurement and sharing can further enhance system stability and reduce overall costs.

By integrating these aspects, the model facilitates improved coordination between interconnected markets, minimises redundancy, and enhances resource utilisation. Ultimately, reserve modelling is not just a tool for short-term system operation—it is a critical component of long-term planning to ensure the European power system remains stable, efficient, and capable of supporting a sustainable energy future.

3.1.9.2. Target

The modelling framework incorporates reserve markets for ancillary services, ensuring that system operators can procure the reserves needed to maintain system reliability. Specifically, the model integrates the procurement of FCR and FRR within the day-ahead market, enabling the co-optimisation of energy and reserves. This ensures that market resources are allocated efficiently between energy and reserves while meeting the system operators' reserve requirements. The technical specifications of each service determine which units can provide the respective products, ensuring feasibility and operational compliance.

The model outputs reserve allocation and pricing, providing detailed information to the assessment of NPV estimations for reserve providers through their revenue streams. These results also serve as an input to the intraday market, determining the amount of reserved capacity is made available for further activation, and ensuring a dynamic and responsive reserve management approach.

3.1.9.3. Implementation strategy

The ancillary services considered in this framework include Frequency Containment Reserve (FCR) and Frequency Restoration Reserve (FRR). These frequency control products play distinct roles in maintaining system stability and restoring frequency deviations, each with specific operational characteristics. In real markets, FRR is subdivided into automatic FRR (aFRR) and manual FRR (mFRR), but the EU-Flex model aggregates them into a single FRR product.

FCR is the fastest-responding service, activated within seconds to stabilise frequency deviations and prevent cascading failures. It is typically symmetric, meaning providers must be capable of both upward and downward regulation. In contrast, FRR is used for frequency restoration: it is activated within minutes to correct deviations and restore system balance. These reserves differ in provision direction (upward and/or downward), activation speed and duration (ranging from seconds to minutes), and capacity requirements (MW).

To accommodate these varying characteristics, the EU-Flex model is designed to be both flexible and technology-agnostic. Users can configure which reserve products to include along with their aggregation level, as well as define their technical parameters. In addition, the model allows users to explicitly define the eligibility of generators, storage units, and demand-side response (DSR) to provide each reserve type and direction. Finally, different reserve procurement methods can be selected, enabling the representation of a wide range of market designs, including co-optimisation, derating approaches, or the absence of explicit reserve procurement.

Since not all technologies can provide every type of reserve, the EU-Flex model explicitly defines the eligibility of generators, DSR, and storage units for each ancillary service. Conventional thermal generators, such as gas and coal plants, typically participate in FCR and FRR, though their ramping constraints may limit the volume they can offer. Hydropower plants, particularly those with fast response capabilities, are well-suited for all reserve types, while pumped storage and batteries excel in FCR and FRR due to their rapid response and high flexibility. Wind and solar assets, despite their variability, can contribute to reserve provision—primarily through downward regulation—depending on forecast accuracy and system needs. Note that, by default, and due to the limited availability of data on eligible reserve providers at the time of writing, all units are assumed to be eligible to provide reserves, although their contribution is naturally constrained by their technical characteristics.

By aligning reserve provision with the technical capabilities of each asset type, the EU-Flex model enhances system reliability while maintaining realistic outcomes. Additionally, its flexible design allows users to simulate different market configurations, from current reserve markets with strict eligibility criteria to future market evolutions that enable broader technology participation. Restricting reserve provision to appropriate technologies is crucial to maintaining realistic results —preventing scenarios where wind and solar provide excessive reserves simply due to large surpluses. This restriction is implemented by defining the eligible technologies within the sets $S^{\mathrm{gen},i,j}$ and $S^{\mathrm{store},i,j}$ for each reserve product i and direction j, or by defining exactly how much reserves each asset provides.

Reserves procurement is modelled using one of two options: a **derating approach**, where a fixed reservation amount is removed from the provision limits of the generators and storage units; or a **co-optimisation approach**, where energy and reserves are jointly optimised within the day-ahead market. For completeness and testing, the EU-Flex tool also includes a **none option**, where reserves procurement is not considered in the market models.

In the **derating approach**, each unit is assigned a predefined reserve contribution (proportional to its capacity compared to total requirements for that resource type) , which effectively reduces its available capacity in the day-ahead (DA) market. For upward reserves, this is implemented by subtracting the reserved capacity from the unit's maximum output (or discharging limits for storage), thereby "derating" its availability for energy generation. For downward reserves, the reserved amounts are added to the unit's minimum output (or charging limits for storage), effectively reducing its ability to decrease generation or increase consumption. As a result, the

model ensures that sufficient capacity is withheld for reserve provision without explicitly optimising reserve allocation.

Note that this approach reduces model complexity compared to the co-optimisation approach described below. However, it has a key limitation: it does not yield market-clearing prices for reserves, as their allocation is predefined rather than endogenously optimised within the model. Consequently, it implicitly assumes that reserve-providing resources remain economically viable in the absence of explicit reserve revenues, or alternatively, that such revenues are accounted for externally. The latter can be incorporated through the exogenous revenue streams described in Section 3.4.2.

In contrast, the **co-optimisation approach** is achieved by incorporating reserve requirements and provider constraints directly into the DA-UCED. The potential reserve providers include the generators described in Section Generation resources, the storage units in Section Energy storage, and the DSR units in Section Demand and demand-side response.

To enable the co-optimisation of energy and reserves within the day-ahead model, the following equations are formulated: (Note that all variables and parameters except for final outputs are, in practice, also indexed by scenario and target year. For legibility reasons, these indices are not included in the formulation below).

$$\sum_{s \in S^{\text{gen},i,j} \cup S^{\text{store},i,j}} r^{i,j}_{n,s,t} \geq R^{i,j}_{n,t} : \left(\lambda^{i,j}_{n,t}\right) \quad \forall t \in T, \forall n \in N, \forall i \in I, \forall j \in J \tag{5.1}$$

$$g_{n,s,t} + \sum_{i \in I} r^{i,+}_{n,s,t} \leq g^{\max}_{n,s,t} \overline{g}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{gen},i,j} \setminus S^{\text{UC},i,j} \tag{5.2}$$

$$g_{n,s,t} - \sum_{i \in I} r^{i,-}_{n,s,t} \geq g^{\min}_{n,s,t} \overline{g}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{gen},i,j} \setminus S^{\text{UC},i,j} \tag{5.3}$$

$$g_{n,s,t} + \sum_{i \in I} r^{i,+}_{n,s,t} \leq g^{\max}_{n,s,t} \overline{g}_{n,s} u_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{UC},i,j} \tag{5.4}$$

$$g_{n,s,t} - \sum_{i \in I} r^{i,-}_{n,s,t} \geq g^{\min}_{n,s,t} \overline{g}_{n,s} u_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{UC},i,j} \tag{5.5}$$

$$h_{n,s,t} - f_{n,s,t} + \sum_{i \in I} r^{i,+}_{n,s,t} \leq \overline{h}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store},i,j} \tag{5.6}$$

$$h_{n,s,t} - f_{n,s,t} - \sum_{i \in I} r^{i,-}_{n,s,t} \geq -\overline{h}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store},i,j} \tag{5.7}$$

$$r^{i,+}_{n,s,t} \leq pr^{i,+}_{n,s} \overline{g}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{gen},i,j} \tag{5.8}$$

$$r^{i,-}_{n,s,t} \leq pr^{i,-}_{n,s} \overline{g}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{gen},i,j} \tag{5.9}$$

$$\sum_{i \in I} A^{\min,i} r^{i,+}_{n,s,t} \leq soc_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store},i,j} \tag{5.10}$$

$$\sum_{i \in I} A^{\min,i} r^{i,-}_{n,s,t} \leq nh_{n,s} \overline{h}_{n,s} - soc_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store},i,j} \tag{5.11}$$

$$g_{n,s,t} - g_{n,s,t-1} + \sum_{i \in I} r^{i,+}_{n,s,t} \leq ru_{n,s}\overline{g}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{gen},i,j} \setminus S^{\mathrm{UC},i,j} \tag{5.12}$$

$$g_{n,s,t} - g_{n,s,t-1} - \sum_{i \in I} r^{i,-}_{n,s,t} \geq -rd_{n,s}\overline{g}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{gen},i,j} \setminus S^{\mathrm{UC},i,j} \tag{5.13}$$

$$g_{n,s,t} - g_{n,s,t-1} + \sum_{i \in I} r^{i,+}_{n,s,t} \leq \left[ru_{n,s}u_{n,s,t-1} + rusu_{n,s}\left(u_{n,s,t} - u_{n,s,t-1}\right)\right]\overline{g}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{UC},i,j} \tag{5.14}$$

$$g_{n,s,t} - g_{n,s,t-1} - \sum_{i \in I} r^{i,-}_{n,s,t} \geq \left[-rd_{n,s}u_{n,s,t} - rdsd_{n,s}\left(u_{n,s,t-1} - u_{n,s,t}\right)\right]\overline{g}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{UC},i,j} \tag{5.15}$$

In equation (5.1), the reserves requirements ($R^{i,j}_{n,t}$) are satisfied for each service *i*, direction *j*, bidding zone *n* and time *t*. $R^{i,j}_{n,t}$ is based on fixed TSO requirements. The dual variable associated to this equation ($\lambda^{i,j}_{n,t}$) represents the opportunity cost of reserves (or reserve price) and is later used to compute the NPV for reserve provisioning.

Equations (5.2) and (5.3) define the revised operational limits for non-committable generators capable of providing reserves, belonging to the set $S^{\mathrm{gen},i,j} \setminus S^{\mathrm{UC},i,j}$. These equations incorporate reserve amounts alongside dispatch variables and replace Equation (2.1) for this category of generators.

Similarly, equations (5.4) and (5.5) establish the new operational limits for committable generators in the set $S^{\mathrm{UC},i,j}$. Reserve amounts are integrated with dispatch variables, replacing Equation (2.2) for the generators in this set. Only the online generators in the committable set are allowed to provide reserves in this formulation.

Equations (5.6) and (5.7) establish the joint boundaries for the dispatch, uptake, and reserves of storage units that provide reserves, identified in the set $S^{\mathrm{store},i,j}$. These constraints work in conjunction with equations (3.1) and (3.2) to ensure that the operational limits of storage units are respected.

Equations (5.8) and (5.9) define the maximum reserve provision constraints for generators providing reserves, ensuring that reserve provision remains within each unit's feasible operational limits. Specifically, equation (5.8) limits the total upward reserve capacity for service *i* to the maximum reserve provision parameter ($pr^{i,+}_{n,s}$, expressed in per-unit of nominal capacity) multiplied by the unit's nominal capacity $\overline{g}_{n,s}$. Similarly, equation (5.9) constrains the total downward reserve capacity using the corresponding downward provision parameter $pr^{i,-}_{n,s}$.

The maximum reserve provision parameters $pr^{i,+}_{n,s}$ and $pr^{i,-}_{n,s}$ represent the fraction of a generator's nominal capacity that can be allocated to reserve service *i*. For FCR, these parameters are always configured directly based on unit-specific technical characteristics. For FRR (which aggregates aFRR and mFRR), the parameters can either be configured directly or computed from the unit's ramping capability as $pr^{\mathrm{FRR},+}_{n,s} = ru_{n,s} \cdot A^{\mathrm{FRR}}$ and $pr^{\mathrm{FRR},-}_{n,s} = rd_{n,s} \cdot A^{\mathrm{FRR}}$, where $ru_{n,s}$ and $rd_{n,s}$ are the ramp-up and ramp-down rates (per unit of nominal power) and A^{FRR} is the full activation time of the FRR service.

For example, consider a generator with nominal capacity $\overline{g}_{n,s} = 100$ MW and maximum provision parameters $pr^{\mathrm{FCR},+}_{n,s} = 0.05$ (5%), $pr^{\mathrm{FRR},+}_{n,s} = 0.25$ (25%), $pr^{\mathrm{FCR},-}_{n,s} = 0.05$ (5%), and $pr^{\mathrm{FRR},-}_{n,s} = 0.10$ (10%). The corresponding reserve limits would be $r^{\mathrm{FCR},+}_{n,s,t} \leq 5$ MW, $r^{\mathrm{FRR},+}_{n,s,t} \leq 25$ MW, $r^{\mathrm{FCR},-}_{n,s,t} \leq 5$ MW, and $r^{\mathrm{FRR},-}_{n,s,t} \leq 10$ MW.

Equations (5.10) and (5.11) ensure that storage units have sufficient stored energy to provide reserves for the full activation period. These constraints prevent, for instance, an empty storage unit ($soc_{n,s,t} = 0$) from offering upward reserves. Here, $nh_{n,s}\overline{h}_{n,s}$ represents the maximum energy that can be stored in the unit at each time step *t*.

Finally, equations (5.12) and (5.13) substitute the ramping equation (2.7) for non-committable generators providing reserves, while equations (5.14) and (5.15) replace the ramping equation (2.8) for committable generators providing reserves.

> Note: The reserves constraints are only added to the day-ahead market model if the configurable parameter “Reserves option = co-optimised” is selected.
>
> Note: Regardless of the procurement method chosen, reserve blocking is consistently applied in the intraday market. The reserved capacities, whether determined through co-optimisation or specified via the derating approach, are subsequently blocked (either partially or fully) in the intraday stage, as described in Section Market interlinkage and operations subsection 3.3.3.3.

3.2. Pre-optimisation

3.2.1. Storage planning

3.2.1.1. Background

Storage facilities play a crucial role in modern power systems by providing flexibility and helping balance supply and demand across different timescales. These facilities, which include pumped hydro storage, large-scale batteries, and other technologies, operate in a complex environment where they must consider both short-term market opportunities and long-term system needs.

Traditionally, storage operators plan their operations across multiple time horizons. In the short term (hours to days), they respond to market price signals, typically charging (storing energy) during periods of low electricity prices and discharging during high-price periods to maximise economic value. This pattern often aligns with daily demand cycles, where prices are lower during night-time hours with low demand and higher during peak demand periods.

However, longer-term planning (weeks to months) is equally critical, particularly for large-scale storage facilities like pumped hydro. These facilities must consider seasonal patterns in electricity demand, renewable generation variability, and system-wide adequacy needs. For instance, in

regions with significant solar generation, storage facilities might need to maintain higher reserves during winter months when solar production is lower.

The optimal management of medium to long term storage resources necessitates a much longer foresight than that considered for operational decisions in the EU-Flex model. Under a perfect market, they are expected to store energy during periods of lower marginal pricing and release it during hours of higher marginal pricing, exploiting the dynamics of market behaviour. Subsequently, planning storage with such limited foresight would result in storage capacities being discharged very quickly to meet demand in the first few timesteps considered during each market simulation. This is driven by the marginal cost of meeting demand in a particular hour compared to dispatchable generators, not considering the long term impacts on system adequacy. Accordingly, medium to long term storage levels must be set during the pre-optimisation phase to provide energy system flexibility for the entire year.

3.2.1.2. Target

The EU-Flex model sets storage levels as part of the pre-optimisation step for each CY to offset the myopic nature of the rolling horizon procedure used in subsequent steps of the workflow. This helps consider system operation more holistically, ensuring adequacy and flexibility measures are distributed throughout the year. While the implementation described here focuses on hydro in particular, the approach extends easily to other forms of medium- to long-term storage: the storage carriers covered by storage planning are set in the configuration (`preopt_targeted_carriers`). The storage planning horizon is configurable by the user and aligned with the rolling horizon resolution. This is typically expected to be in the range of a few days to a week, depending on the desired resolution and computational intensity of a model run. In summary, this means that the number of fixing points must at least equal to the number of (non-overlapping) rolling horizons (RHs).

3.2.1.3. Implementation strategy

The general implementation strategy for medium to long term storage planning is to run a coarse resolution ED model with perfect *foresight*, for each CY. Subsequently, the pre-optimisation identifies the optimal operation of medium to long term storage assets, allowing targets to be set on storage levels at different time intervals in the market models. These targets are used as the starting point (i.e. the values at the first hour of each RH), upon which the UCED sub-problem determines the final generation per horizon, also considering the realised availability of other resources or loads. This is captured by **Figure 4** below. The flowchart shows how all the primary inputs to the main market simulation are used, but the coarse resolution pre-optimisation model is used to extract the storage planning strategy.

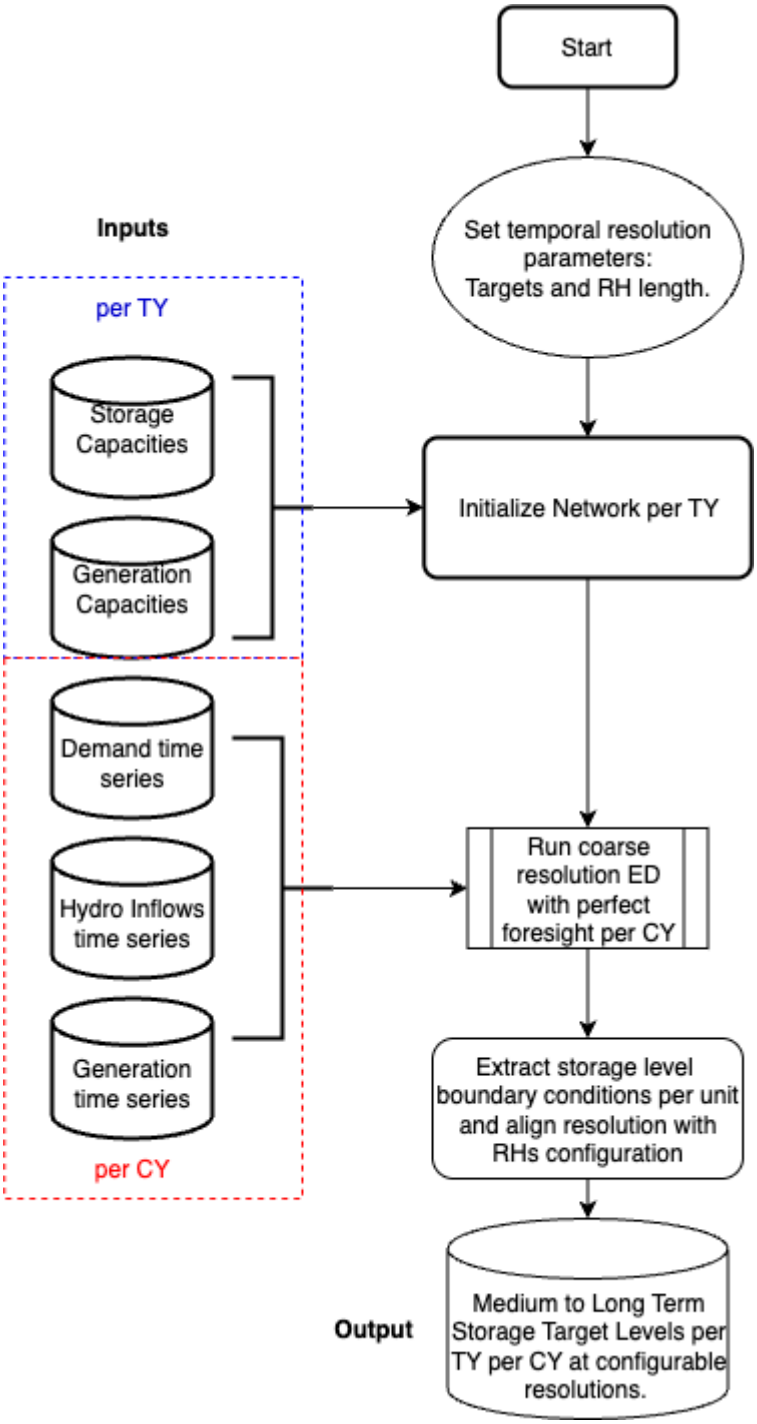


Figure 4: Overview of pre-optimisation step for storage planning in EU-Flex.

The storage planning pre-optimisation is initially performed once for every CY in each TY, although a configurable parameter (*frequency of storage planning updates*) can be used to determine how often to re-run it during the EVA loop. The objective function for the pre-optimisation model, including primary constraints, is presented in its full mathematical formulation in Section Market definitions and components without unit commitment features. While this is not repeated in this section for conciseness, it should be noted that the only difference is a horizon of 1-year as opposed to user defined one (detailed in Section Market simulation) with the objective still representing minimisation of cumulative system costs to meet electricity demand. This considers

dispatch costs and storage costs with dispatch and/or uptake for all technologies. The full mathematical formulation of storage assets is given in Section Energy storage) above. The objective for the pre-optimisation is thus defined according to (6.1), or the minimisation of total system costs considering all technological components. The storage levels $soc_{n,s,t}$ were previously defined by (3.5), considering efficiency of storage and discharge, as well as inflow and spillage (where applicable). Note that all other constraints presented in the Market Simulation sections also apply here at the time of writing, but they are not included in this section to focus on the key aspects covered by the pre optimisation.

$$\min \sum_{n,s,t} c_{n,s} \left(g_{n,s,t'} m_{n,s,t'} h_{n,s,t} \right) \tag{6.1}$$

$$soc_{n,s,t}^{\mathrm{POtarget}} = soc_{n,s,t}^{*} \quad \forall t \in T^{\mathrm{RH-end}}, \forall n \in N, \forall s \in S^{\mathrm{LTS}} \tag{6.2}$$

The result of this model is a set of optimal state-of-charges for every end of the market model's rolling horizon, i.e., $soc_{n,s,t}^{*} \forall t \in T^{\mathrm{RH-end}}$. As shown by (6.2), the optimal storage levels from the ED described above then determine the target storage levels $soc_{n,s,t}^{\mathrm{POtarget}}$ which are in turn included in the DA/ID market models, as further detailed in Section Market simulation.

The approach depicted in **Figure 4** and equations (6.1)-(6.2) is designed to be modular and applicable to different forms of storage, and the storage carriers it covers are configurable. Nonetheless, the management of hydro storage resources was a primary driver to the need of a pre-optimisation step. In fact, hydro storage optimisation is particularly complex as it is constrained by both hourly generation capacity and available stored energy, considering any additional cumulative energy flows (i.e. hydro inflows). Furthermore, individual site level data is not available to estimate the impact of coupling and second order effects among plants and reservoirs. In order to minimise the computational expense of this step, as combined with data availability restrictions, the same technological aggregation strategy as for the PECD hydro database[14] is followed, as summarised by **Table 4**. This approach can be adapted based on changing data availability.

Table 4: Overview of hydro technologies considered in the EU-Flex model

Category	Reservoir	Storage Capacity[15]	Pumping Capacity	Natural Inflows	PECD Data Resolution
Run-of-River and Pondage	No	No or <24 hours	No	Yes	Daily
Reservoir	Yes	>24 hours	No	Yes	Weekly
Open-loop Pumped Storage	Yes	>24 hours	Yes	Yes	Weekly
Closed-loop Pumped Storage	Yes	>24 hours	Yes	No	Weekly

Table 4 lists all hydro technologies of the PECD hydro database for completeness, but not all of them are planned in this step. Following the ERAA methodology, RoR and Pondage are not considered as storage assets in the storage planning, as their storage capacity is small relative to their generation capacity (no storage, or less than 24 hours). Only reservoirs and open- and closed-loop pumped storage receive target storage levels. Hydro inflows are available in weekly energy lots for the storage assets considered in this section, which are assumed to be equally distributed over 168 hours. The available energy is then released according to system needs based on the selected resolution to generate the boundary conditions at the desired resolution. It is again noted that the number of fixed points (i.e., target storage levels) must **be at least equal** to the non-overlapping number of RHs. If available hourly inflows exceed the dispatch needs or the maximum reservoir level trajectories, the EU-Flex model spills the inflow surplus. Furthermore, in addition to target levels trajectories, minimum and maximum levels are provided as hard constraints from the PECD hydropower modelling database.

3.2.2. Maintenance planning

3.2.2.1. Background

Planned maintenance of generators is essential to ensure their reliability, efficiency, and longevity. Regular upkeep helps reduce the likelihood of unexpected breakdowns, which can lead to costly repairs, operational downtime, and even power outages. In the context of the proposed flexibility assessment periodic maintenance should be explicitly accounted for to reduce risks of unavailability for dispatchable thermal capacity. This is particularly relevant to minimise disruptions for periods with inadequacy risks, typically characterised by higher load compared to generation capacity. Furthermore, following this approach minimises the disruptions caused by unplanned or forced outages, which are stochastically introduced in the EU-Flex model as described in Section Monte Carlo sampling.

3.2.2.2. Target

The EU-Flex model explicitly considers maintenance planning during the pre-optimisation step on a per target year (TY) basis. The objective is to maximise availability of dispatchable generation during times of reduced system adequacy, considering the forecasted demand and renewable energy production at each bidding zone. Hourly maintenance profiles are thus produced on a per-unit basis, allowing more flexibility on how to distribute maintenance requirements across the year and not lead to excessive shortages in any one period. The ENTSO-E maintenance planning methodology[17] is followed, aiming to level the weekly capacity margin per BZ based on planned annual outage rates for each unit.

3.2.2.3. Implementation strategy

The planned maintenance schedule is optimised for each year during the pre-optimisation step by first considering a yearly horizon T^{maint} with perfect foresight. The maintenance scheduling is performed for a subset of thermal generator units $S^{\text{maint}} \in S^{\text{gen}}$. The annual planned outage rates $POR_{n,s}$ for each unit (or technology type) *s* is the primary input considered here, defined as shown in (7.1), where $DAYS_{n,s}$ captures the total number of days per year required for maintenance. The net capacity margin $cm_{n,d}$ at day *d* can then be defined according to (7.2), across all generating units for each BZ *n*. $\overline{g}_{n,s}$ denotes the installed generating capacity and $y_{n,s,d}$ the binary maintenance status of each unit on day *d* ('1' means the unit is in maintenance and unavailable, '0' means it is fully available). $RL^{\text{peak}}_{n,d}$ shows the peak estimated residual load at day *d* for BZ *n*, which is used for maintenance planning purposes as expected renewable production must be taken into account to minimise system scarcity risk. Accordingly, the residual load profile is found following the ENTSO-E methodology as captured by (7.3). The maximum native *daily* demand over all CYs $D^{\text{max,CY}}_{n,d}$ is taken as a starting point, from which the minimum renewable generation over the same CYs $G^{\text{min,VRE,CY}}_{n,d}$, is subtracted. This is done on a per BZ basis, neglecting the impact or availability of cross-border interconnection capacities. Note that $cm_{n,d}$ is computed with a daily resolution to align with the optimisation of daily maintenance schedules for thermal generators.

$$POR_{n,s} = \frac{DAYS_{n,s}}{365} \quad \forall n \in N, \forall s \in S^{\text{maint}} \tag{7.1}$$

$$cm_{n,d} = \sum_{s \in S^{\text{maint}}} \overline{g}_{n,s} \left(1 - y_{n,s,d}\right) - RL^{\text{peak}}_{n,d} \quad \forall n \in N, \forall d \in T^{\text{maint}} \tag{7.2}$$

$$RL^{\text{peak}}_{n,d} = D^{\text{max,CY}}_{n,d} - G^{\text{min,VRE,CY}}_{n,d} \quad \forall n \in N, \forall d \in T^{\text{maint}} \tag{7.3}$$

For new units (those with `is_existing=False`), maintenance is scheduled based on inverse residual load rather than through the optimisation procedure described below. This approach applies higher unavailability during periods of low residual load (high renewable availability), distributing maintenance proportionally across all hours while respecting the planned outage rate. The unavailability fraction $y^{\text{new}}_{n,s,t}$ for new generator *s* at time *t* is calculated as:

$$y^{\text{new}}_{n,s,t} = \frac{RL^{-1}_{n,t}}{\sum_{t' \in T^{\text{maint}}} RL^{-1}_{n,t'}} \cdot POR_{n,s} \cdot 24 \quad \forall n \in N, \forall s \in S^{\text{new}}, \forall t \in T^{\text{maint}} \tag{7.4}$$

where $RL^{-1}_{n,t} = 1/(RL_{n,t} + \epsilon)$ is the inverse residual load (with small ϵ to avoid division by zero) and $RL_{n,t}$ is the average residual load across climate years. The unavailability fraction is clipped to $[0, 1]$ and normalised to maintain the total planned outage rate.

The objective function for maintenance planning (for existing units) can then be defined as:

$$\min \sum_{d \in T^{\text{maint}}} cm^2_{n,d} \tag{7.5}$$

s.t.

$$\sum_{d=T^e_{n,s}}^{T^l_{n,s}} x_{n,s,d} = 1 \quad \forall n \in N, \forall s \in S^{\text{maint}} \tag{7.6}$$

$$\sum_{d=T^e_{n,s}}^{T^l_{n,s}+\text{DAYS}_{n,s}-1} y_{n,s,d} = DAYS_{n,s} \quad \forall n \in N, \forall s \in S^{\text{maint}} \tag{7.7}$$

$$y_{n,s,d} - y_{n,s,d-1} \leq x_{n,s,d} \quad \forall n \in N, \forall s \in S^{\text{maint}}, \forall d \in T^{\text{maint}} \tag{7.8}$$

$$\sum_{s \in S^{\text{maint}}_k} y_{n,s,d} \leq k_k \quad \forall d \in T, k \in SK \tag{7.9}$$

where:

- (7.6) shows maintenance is allowed only once per planning horizon.
- (7.7) ensures maintenance of generating units lasts for a pre-specified duration.
- (7.8) limits maintenance of each generating unit to happen over. consecutive/uninterrupted time periods.
- (7.9) is an exclusion constraint to prevent certain units from being in maintenance simultaneously.

The result of this model is a set of optimal maintenance plans ($y^*_{n,s,d}$) for the units in $s \in S^{\text{maint}}$, and they are calculated per TY at a daily resolution. In the DA and ID market models, the dispatch bounds $g^{\min}_{n,s,t}$ and $g^{\max}_{n,s,t}$ of each unit in (2.1) and (2.2) are scaled by its availability $1 - y^*_{n,s,t}$, where $y^*_{n,s,t}$ takes the value of the plan on the day containing hour t (for new units, the hourly unavailability fraction from (7.4)). See (10.2).

The minimisation of the objective described above can be obtained with the Simulated Annealing (SA) algorithm, as it has been previously widely applied in the literature[18] [19] [20] for similar problems. The high-level overview of the proposed algorithmic approach is captured by **Figure 5** below, highlighting similarities to the process described by ENTSO-E.

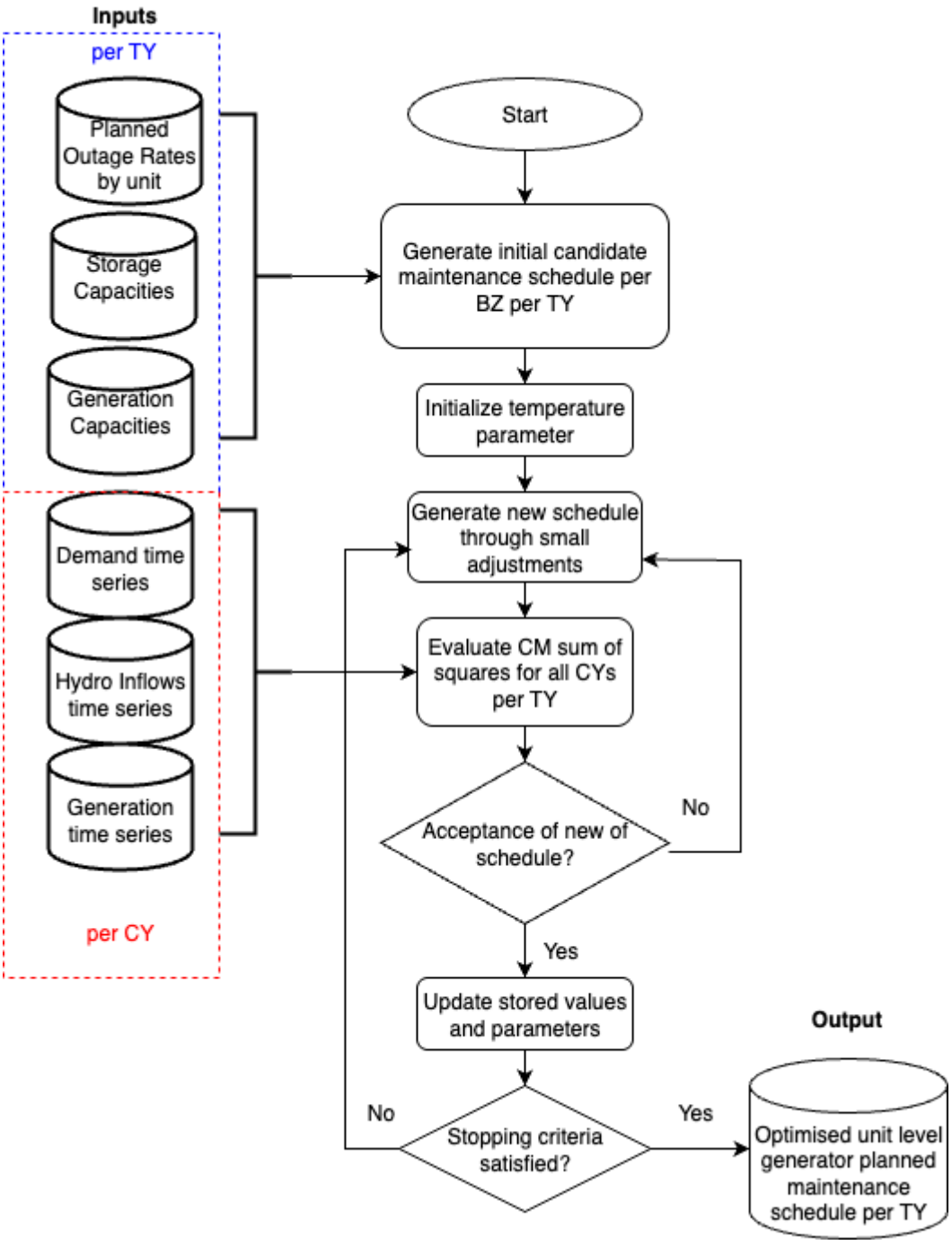


Figure 5: Overview of SA procedure for maintenance planning.

Simulated annealing is a metaheuristic optimisation algorithm that can effectively address generator maintenance scheduling problems by exploring a wide solution space while avoiding local optima. This mechanism mimics the physical annealing process in metallurgy, where controlled cooling helps materials reach a stable, low-energy state—analogous to finding an optimal or near-optimal maintenance schedule with a leveled capacity margin.The algorithm iteratively adjusts the maintenance schedule of generators, guided by an objective function that aims to level out the capacity margin, considering a key temperature parameter. In the context of simulated annealing for generator maintenance scheduling, the *temperature* is a control parameter that influences the probability of accepting worse solutions during the search process.

Initially set to a high value, the temperature allows the algorithm to explore the solution space broadly, accepting suboptimal schedules to escape local optima. As the temperature gradually decreases according to a predefined cooling schedule, the algorithm becomes more selective, favouring only improvements or minor deterioration, helping level out capacity margin in each BZ and ensuring a balanced distribution of available generation capacity over time.

The maintenance profiles can be initialised to be randomly distributed in the summer months, when scarcity risks are generally lowest, and then gradually adjusted to level out the capacity margin. The constraints described above are implemented in the initialisation as well, meaning any redistribution of maintenance periods still ensures the planned outage rates ($POR_{n,s}$) described above are achieved for each unit or technology type, depending on the configured resolution.

3.3. Market simulation

3.3.1. Monte Carlo sampling

3.3.1.1. Background

Energy systems face multiple sources of uncertainty that impact flexibility needs, market operations, and long-term planning. Short-term uncertainties, such as fluctuations in weather and electricity demand, affect market operations. While day-ahead markets rely on forecasts, intra-day markets incorporate real-time updates, requiring flexible resources to balance deviations. Long-term climate variability influences electricity supply and demand, impacting capacity margins and system adequacy. Accounting for these variations is crucial for reliable long-term planning. Resource availability uncertainty extends beyond climate conditions and planned maintenance, affecting generation, storage, and transmission assets. Scenario-based analyses help mitigate risks and ensure system resilience.

Effectively addressing these uncertainties is key to enhancing system flexibility, market efficiency, and the overall stability of the energy transition.

3.3.1.2. Target

The EU-Flex model includes these different types of uncertainty in three different ways

1. Short-term uncertainty about weather conditions and demand. These are taken into account through the use of two different market models, one for the day-ahead market, and one for the intra-day market. Day-ahead markets are cleared using weather and demand forecasts, while intra-day markets are cleared using actual realisations of weather and demand. Differences

between forecasts and realisations have to be compensated for by flexible demand- or supply-side technologies. This is further described in the modelling sections above.

2. Long-term variation about climate conditions. Climate variables affect supply of and demand for electricity. Different years have different weather patterns, which affect capacity margins, behaviour of flexible resources, and overall adequacy of the system. The EU-Flex model takes these longer-term uncertainties into account through the use of climate scenarios. This is further described in this section.

3. Uncertainty about the availability of generation, storage and transmission resources for reasons other than climate conditions or planned outages. The EU-Flex model also uses scenarios to take this type of uncertainty into account. This is further described in this section. Note that planned outages are not uncertain; these are included in the pre-optimisation module, as described above.

More specifically, the EU-Flex model is based on a probabilistic approach to reflect the stochasticity of climate variables affecting supply and demand (i.e., various CYs), as well as the expected availability of generation, storage and transmission resources (i.e., various outage profiles). The tool incorporates the stochasticity of the aforementioned parameters through Monte Carlo analysis. It generates a set of scenarios, which is the Cartesian product of a set of CYs, and a set of outage realisations, based on random draws from independent outage distributions of individual components. These scenarios are then used in the market models, with the climate realisations being used in both the DA and ID models, and the random outages being used only in the ID model. It is possible for the user to select a subset of conditions reflecting the stochasticity of the aforementioned parameters (e.g., number of CYs) for performing the assessment. By being able to set the seed for all random processes, it is possible to generate the same random scenarios to run the assessment for quality assurance purposes and evaluate the impact of changes to the inputs.

3.3.1.3. Implementation strategy

Users can optionally set the random seed for the scenario generation process, via a configurable parameter (Random seed for forced outages), allowing for reproducibility. Python's built-in Mersenne Twister generator is used to generate all random numbers. Users can also enable/disable the addition of forced outages via the configurable parameter "Enable forced outages".

First, users manually select a set of climate years (CYs), which are equiprobable, i.e., $(PR_{\text{cy}} = 1/|CY|, \forall cy \in CY)$.

Second, a set of outage scenarios *OS* is generated, with a size *|OS|* set by the user. We assume that outage probabilities for (disaggregated) generation, storage, and transmission resources follow independent Bernoulli distributions for each unit for each 24-hour period, with averages

defined by the Forced Outage Rate (FOR) of the unit. Using this assumption, *OS* is constructed as follows:

1. For each snapshot, a Poisson sample of units experiencing the start of a forced outage event is drawn using the user-specified sample size. For generation and storage, we do this either a) using the disaggregated set of generators and storage facilities, aggregating capacities at each location only later; or b) if the disaggregated set of generators is not available, by dividing the total generation capacity of a specific type by the number of units for that same type estimated from the DB, assuming equal size. For transmission, we use the set of cross-zonal interconnectors, with independent sampling for each pole. Only NTC interconnectors are used for outage sampling, as flow-based domains are already N-1 secure and implicitly include outages within their data.

2. After sampling units (set S^{FOR}) and interconnectors (set L^{FOR}) that are unavailable, those units are no longer sampled for outage events until the event is over.

3. The outage duration for each affected unit is assigned based on the default values from ERAA, unless more specific data is provided, starting from the sampled hour and continuing until the end of the outage duration. If the outage extends beyond the remaining hours of the 24-hour period, it continues into the following periods until its full duration is reached. Outage durations are by default 7 days for nuclear generators and interconnectors, while 24 hours for all other assets.

4. The total unavailable capacity for each technology type in each bidding zone is calculated by summing the unavailable capacities of the sampled units and interconnectors. This total is then divided by the corresponding installed capacity in the same bidding zone to obtain the fraction of capacity unavailable due to forced outages ($y^{\mathrm{FOR}}_{n,s,t}$ for generators and storage and $y^{\mathrm{FOR}}_{l,t}$ for interconnectors). This operation is performed to convert the outage data into the format used in the market model.

5. These fractional forced unavailability factors are then joined together to form a time series with hourly resolution, containing the fraction of capacity of each type in each bidding zone in each 24-hour period that is unavailable because of forced outages.

For model runs in which a Monte Carlo Simulation using a large number of outage scenarios is not needed, users can manually populate *OS* with a single scenario in which the fraction of each type of capacity unavailable because of forced outages is equal to its FOR. We note that outages are considered to happen in the intraday market only.

The total set of scenarios SY is the Cartesian project of *OS* and *CY*. The total number of scenarios that are modelled is therefore equal to *|CY||OS|*. Because outage scenarios are equiprobable, weights for each scenario $sy \in SY$ are given by:

$$PR_{\mathrm{sy}} = \sum_{\mathrm{cy}} \frac{PR_{\mathrm{cy}}}{|OS|} cs_{\mathrm{cy,sy}} \quad \forall sy \in SY \tag{8.1}$$

where $cs_{\mathrm{cy,sy}}$ is a dummy parameter equal to 1 if *sy* uses weather year *cy*, and 0 otherwise.

These scenarios are used in the market models, with the climate realisations being used in both the DA and ID models, and the random outages being used only in the ID model.

3.3.2. Market definitions and components

3.3.2.1. Background

The European electricity market operates through a sequential scheduling process that ensures cost-effective and reliable power system operation. The Day-Ahead Market serves as the primary scheduling mechanism, where electricity generation and consumption for the following day are determined based on forecasted supply, demand, and system constraints. This market assumes perfect foresight, optimising unit commitment and dispatch decisions in advance. However, due to forecast errors, renewable variability, and unexpected outages, real-time adjustments are necessary. The Intraday Market refines the dispatch schedule in response to deviations, exploiting system flexibility within operational constraints.

3.3.2.2. Target

The EU-Flex model implements a two-stage market modelling framework to optimise short-term generation scheduling and dispatch while optimising system adequacy, economic efficiency, and operational reliability under increasing shares of VRE. This framework consists of:

1. Day-Ahead Unit Commitment and Economic Dispatch (DA-UCED): Optimises unit commitment, dispatch, and reserves decisions for the day-ahead market, ensuring cost-effective scheduling of generation while considering system constraints.

2. Intraday and Balancing Economic Dispatch (ID-ED): Adjusts generation dispatch schedules based on updated demand, VRE availability, and forced outages, while keeping DA commitment decisions fixed, and reserves (totally or partially) blocked.

3.3.2.3. Implementation strategy

The modelling framework employs an iterative market-clearing process, where DA-UCED sets the initial dispatch plan, and ID-ED adjusts schedules to reflect real-time conditions. A rolling horizon approach is used, where commitment and dispatch decisions are calculated over overlapping time blocks, balancing forecast accuracy with computational efficiency. More specifically, these models run sequentially for each rolling horizon ($\forall ro \in RO$) within a target year ($\forall ty \in TY$) for each scenario ($\forall sy \in SY$). Additionally, all target years and scenarios are executed independently. This is explained more in detail in Section Market interlinkage and operations.

Together, DA-UCED and ID-ED ensure cost-efficient and reliable power system operation, balancing proactive scheduling with the flexibility to respond to real-time deviations. This process is governed by a comprehensive set of technical and economic constraints, ensuring that unit commitment, dispatch optimisation, real-time adjustments, and reserve allocations remain physically feasible and economically justified.

The DA-UCED model optimally determines unit commitment (on/off status), operating levels, and reserve allocations to minimise total system costs while adhering to key constraints, including:

- Transmission network constraints between bidding zones, including NTC and FBMC models.
- Minimum up/downtimes, ramp rates, capacity limits, startup and shutdown costs, and minimum stable output level for generators.
- Forecasted renewable generators availability and forecasted demand.
- Planned maintenance schedules from the pre-optimisation phase.
- Storage constraints and costs.
- Storage limits set in the pre-optimisation phase, ensuring strategic use of storage resources across all RHs considered.
- Explicit and implicit demand-side response constraints and costs.
- Loss-of-load costs.
- Ancillary services requirements and allocation constraints.

The ID-ED model fine-tunes dispatch schedules in response to real-time market conditions while incorporating results of the day-ahead market. It dynamically adjusts dispatch levels to:

- Accommodate realised VRE generation and updated demand based on short-term forecasts and real-time deviations from the CY scenario.
- Incorporate for forced outage scenarios.
- Maintain unit commitment decisions from the day-ahead market.
- Adhere to reserved capacity allocations from the day-ahead market, either partially or fully.

To solve both models efficiently, standard solvers such as Gurobi, CPLEX, and HiGHS are used, ensuring computational feasibility and scalability for large-scale power system models. This optimisation approach follows practices outlined in well-established publications[21], ensuring realistic market and operational behaviour.

3.3.2.4. Mathematical formulation of DA-UCED

The DA-UCED is a Mixed-Integer Linear Programming (MILP) model designed to optimise asset dispatch, unit commitments, and reserve allocations, all with the goal of minimising total system costs. The formulation below captures the equations governing the DA-UCED model. It represents the operation of the DA-UCED for a single rolling horizon ($ro \in RO$), target year ($ty \in TY$), and scenario ($sy \in SY$).

For simplicity and clarity, the indices corresponding to these time frames and scenarios are omitted from the notation in this section. The following sections show how the results of the multiple runs of this model are collected and utilised to calculate key metrics and inform subsequent processes.

$$\begin{aligned}\min \quad & \sum_{n\in N}\sum_{s\in S^{\text{gen}}}\sum_{t\in T} MC_{n,s,t}g_{n,s,t} + \sum_{n\in N}\sum_{s\in S^{\text{UC}}}\sum_{t\in T}(suc_{n,s,t}+sdc_{n,s,t}) \\ & + \sum_{t\in T} w_t\left(\sum_{n\in N}\sum_{s\in S^{\text{store}}} MC_{n,s,t}h_{n,s,t}\right) \\ & + \sum_{n\in N}\sum_{s\in S^{\text{exDSR}}}\sum_{t\in T} MC_{n,s,t}g_{n,s,t} + \sum_{n\in N}\sum_{s\in S^{\text{lolDSR}}}\sum_{t\in T} VoLL_{n,s,t}g_{n,s,t}\end{aligned} \tag{10.1}$$

s.t.

Network constraints: (1.1)-(1.5)

Generators constraints: (2.1)-(2.9)

Maintenance planning:

$$g^{\max}_{n,s,t} \leftarrow \left(1-y^{*}_{n,s,t}\right) g^{\max}_{n,s,t}, \quad g^{\min}_{n,s,t} \leftarrow \left(1-y^{*}_{n,s,t}\right) g^{\min}_{n,s,t} \quad \forall t\in T, \forall n\in N, \forall s\in S^{\text{maint}} \tag{10.2}$$

Storage constraints: (3.1)-(3.5)

Storage boundary constraints:

$$soc_{n,s,t} \geq soc^{\text{POtarget}}_{n,s,t} \quad \text{if } t\in T^{\text{RH-end}}, \forall n\in N, \forall s\in S^{\text{LTS}} \tag{10.3}$$

Implicit DSR constraints: (3.1)-(3.5), (4.1)-(4.3) $\forall s \in S^{\text{imDSR}}$

Explicit DSR constraints: (2.1), (2.7), (4.4)[optional], (4.5)[optional] $\forall s \in S^{\text{exDSR}} \cup S^{\text{lolDSR}}$

Reserves constraints: (5.1)-(5.15) [or fixed values for derating]

The objective function in equation (10.1) minimises the total cost of the DA-UCED. It includes the following components:

- Dispatch Costs: related to the generation, including fuel, CO_2 emissions, and variable operational costs per MWh (all integrated in the marginal costs of the generators $MC_{n,s,t}$).

- Startup and Shutdown Costs: incurred when a generator transitions from OFF to ON, and from ON to OFF, respectively.
- Storage costs: related to certain storage units with an associated cost for dispatch.
- Explicit DSR costs: related to the marginal cost of the explicit DSR units providing demand shifting/shedding to the market.
- Loss-of-load costs: related to the demand shedding DSR representing the loss-of-load in each bidding zone. The dispatch cost of this unit is calculated as the VoLL, which is also expected to represent the market price cap.
- Reserve costs (optional): a small penalty cost for reserve provision can be added to the objective function to avoid unnecessary over-procurement of reserves.

The model's constraints are outlined in Sections Network graph and transmission, Generation resources, Energy storage, Demand and demand-side response, and Ancillary services and reserves management. Additionally, equation (10.2) incorporates the maintenance plans of assets $\forall s \in S^{\text{maint}}$, updating their availability based on the results from the pre-optimisation phase. Finally, equation (10.3) ensures that the storage state-of-charge remains within the boundary conditions established during the pre-optimisation process.

> Note: Instead of the mixed-integer formulation above, a linearised unit commitment can be used for faster running, in which the commitment variables are relaxed to continuous values. The simple linearised unit commitment is the option used in the assessment. Optionally, the linearised formulation can be tightened with the convex hull relaxation available in [46]. This tightening requires symmetric start-up and shut-down costs (i.e., $c^{\text{su}}_{n,s} = c^{\text{sd}}_{n,s}$) to achieve the tightest LP relaxation. Since ERAA data typically has asymmetric costs, the model automatically symmetrises them when the tightening is enabled by computing:
>
> $$c^{\text{su,sym}}_{n,s} = c^{\text{sd,sym}}_{n,s} = \frac{c^{\text{su}}_{n,s} + c^{\text{sd}}_{n,s}}{2}$$
>
> This ensures the convex hull tightening constraints are properly applied, achieving near-optimal solutions (typically within 0.04% of MILP) while maintaining LP computational efficiency.

3.3.2.5. Mathematical formulation of ID-ED

The ID-ED formulation primarily adjusts dispatch levels in response to real-time fluctuations while incorporating updates on transmission constraints, renewable energy availability, short-term demand forecasts, and ancillary services allocation. Unlike DA-UCED, it keeps the unit commitments of most committable generators fixed and optimally redistributes the available capacity to enhance system operation. Generators of the carriers listed in `id_free_commitment_carriers` (set $S^{\text{UC,free}}$; by default gas, hydrogen and oil units and explicit

DSR) can re-commit in ID-ED, while the commitment of all other committable generators (set $S^{\text{UC,fixed}}$) is fixed to the DA-UCED result. ID-ED always uses the linearised unit commitment formulation, so it involves only continuous variables and is a Linear Programming (LP) problem.

While ID-ED follows the same objective function and equations as DA-UCED, it differs in its treatment of committable resources and reserves. DA-UCED jointly optimises unit commitment and dispatch, explicitly considering startup and shutdown costs through the binary variables $u_{n,s,t}$. In contrast, ID-ED fixes the commitment of the generators in $S^{\text{UC,fixed}}$, so these incur no additional start-up or shut-down costs. Only the generators in $S^{\text{UC,free}}$ can start up or shut down in ID-ED, at their usual start-up and shut-down costs. Additionally, ID-ED does not include the ancillary services allocation model of Section 3.1.9: reserves are procured once, in DA-UCED, ahead of real time, so the reserve variables $r^{i,j}_{n,s,t}$ and the reserve requirement (5.1) are not part of ID-ED. Instead, the reserves allocated in DA-UCED enter ID-ED as fixed values, and the share of them that is blocked in the intraday stage (equations (9.6)-(9.8) in Section 3.3.3.3) reduces the capacity available for intraday dispatch.

Mathematically, for $s \in S^{\text{UC,fixed}}$ the commitment variables $u_{n,s,t}$ are fixed to the DA-UCED results, which excludes their start-up and shut-down costs and omits equations (2.5) and (2.6); the minimum up/down time constraints (2.3) and (2.4) are respected by the fixed DA commitment and not re-optimised. For $s \in S^{\text{UC,free}}$, $u_{n,s,t}$ is a continuous variable in $[0, 1]$ and equations (2.2)-(2.6) apply as in the linearised unit commitment formulation of DA-UCED. ID-ED dynamically applies ramping limits (2.7) and (2.8) without altering commitment status, and dispatch levels for committable units must adhere to must-run constraints (2.9). Equations (1.1)-(1.2) ensure real-time power balance by incorporating updated renewable generation and demand conditions, while equations (1.3)-(1.5) adjust congestion management dynamically. Moreover, the reserve variables are fixed to the blocked share of the reserves allocated in DA-UCED, depending on whether these are blocked fully, partially, or not at all in the ID model: the blocked reserves reduce the dispatch limits of generators and enter the storage limits (5.6) and (5.7) as fixed values, and, if reserves are co-optimised, they also reduce the ramping limits through equations (5.12)-(5.15). Finally, the availability of generators and storage in set S^{FOR}, and of interconnectors in set L^{FOR} is updated according to the forced outage values $y^{\text{FOR}}_{n,s,t}$ and $y^{\text{FOR}}_{l,t}$ of scenario $sy \in SY$.

3.3.3. Market interlinkage and operations

3.3.3.1. Background

To accurately assess flexibility needs, it is essential to reflect the structure of real-world electricity markets, typically segmented into day-ahead, intraday, and real-time markets. The day-ahead market sets an initial commitment and dispatch schedule based on forecasts, while the intraday and real-time markets facilitate adjustments to correct forecast errors, manage renewable variability, respond to unplanned outages, and address deviations from the day-ahead schedule.

This structured market coordination is fundamental for enhancing forecasting accuracy, real-time balancing, reserve management, and the efficient deployment of system flexibility.

3.3.3.2. Target

The EU-Flex model establishes an integrated market framework that aligns day-ahead scheduling with intra-day dispatch adjustments, mirroring the structure of real-world electricity markets. By coupling the DA-UCED and ID-ED models, it provides a realistic, economically efficient, and operationally robust approach to managing system uncertainties while maintaining reliability and cost-effectiveness. It ensures:

- Seamless coordination between DA-UCED and ID-ED, enabling efficient short-term decision-making.
- Effective information transfer, ensuring real-time adjustments to generation schedules, reserve deployment, and congestion management reflect the latest system conditions.
- Enhanced system reliability, with mechanisms for reserve activation, congestion mitigation, and real-time demand balancing.

This integrated framework emulates real-world market dynamics, improving efficiency, security, and economic viability in power system operations, particularly as renewable energy penetration and demand variability increase.

3.3.3.3. Implementation strategy

The EU-Flex model follows a sequential optimisation procedure, where pre-optimisation establishes long-term storage and commitment constraints, DA-UCED determines the initial dispatch schedule and reserve allocation, and ID-ED refines real-time operations and reserves deployment. This layered approach ensures stable yet adaptable market operations, optimising generation scheduling, reserve deployment, congestion management, and cross-zonal coordination in the face of increasing renewable energy penetration.

To implement this framework, a rolling horizon approach is applied, enabling the market models to run sequentially. Each rolling horizon spans *T* time slots, with an overlapping segment that is re-evaluated in the subsequent market session to ensure computational efficiency and solution feasibility. A subset of *T'* time steps is retained from each run, meaning the overlap between consecutive horizons is *T-T'*.

The DA-UCED and ID-ED models are executed sequentially for each rolling horizon, within a given target year (TY) and scenario (SY). The results of DA-UCED directly inform the ID-ED calculations, ensuring consistency in unit commitments and reserve allocation. Additionally, boundary conditions from one rolling horizon are carried forward to the next, maintaining continuity across time steps. This process continues until all rolling horizons within the target year ($\forall ro \in RO$) are completed. **Figure 6** illustrates this sequential process.

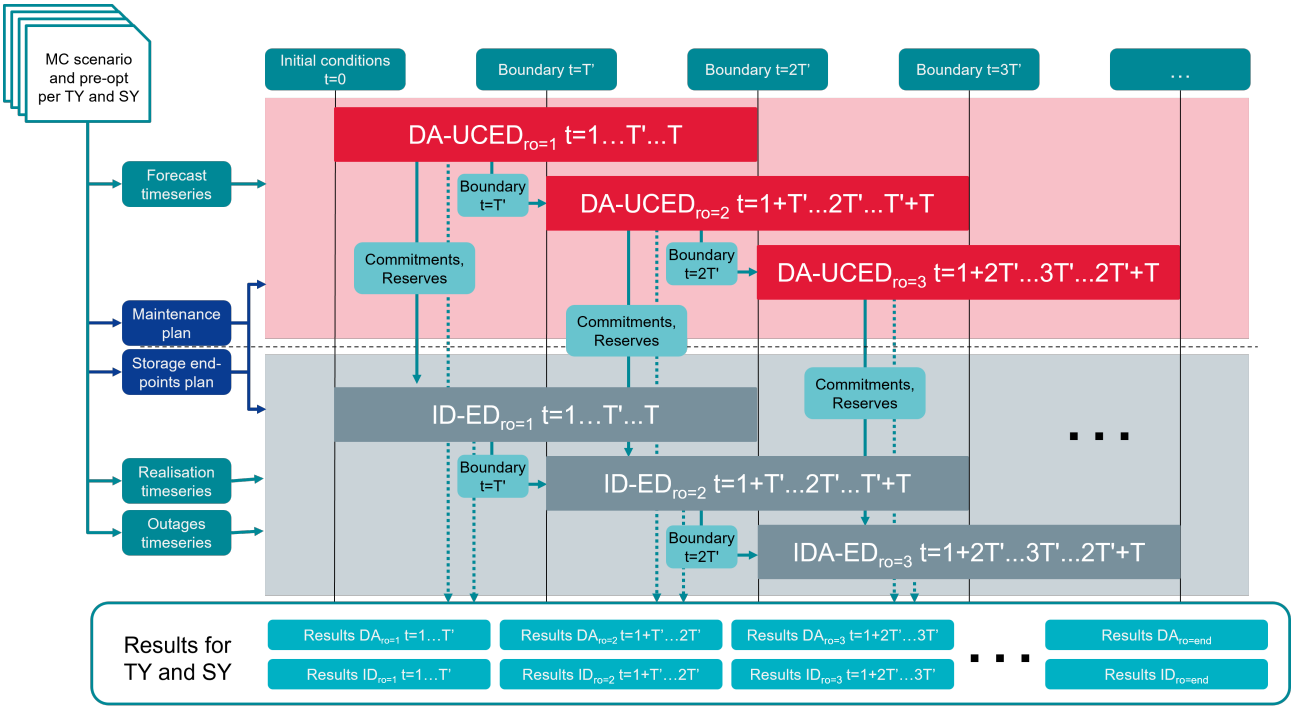


Figure 6: Interlinkage of market models in the rolling horizon approach.

For each rolling horizon ($\forall ro \in RO$), the DA-UCED model determines unit commitments and dispatch schedules, optimising market outcomes based on forecasted demand, renewable availability, and system constraints outlined in Section Market definitions and components. Specifically, it relies on scenario-based forecasts for a given TY and SY. Additionally, pre-optimisation results define asset availability by incorporating planned maintenance schedules ($y^{*}_{n,s,t}$ for $s \in S^{\text{maint}}$), and establishing boundary conditions ($soc^{\text{DA/ID}}_{n,s,t}$ for $t \in T^{\text{RH-end}}$ for $s \in S^{\text{LTS}}$) for storage units based on prior storage planning. Once the DA-UCED is executed under this setup, its results—unit commitments and reserve allocations—are passed to the ID-ED model.

The ID-ED model operates with the same pre-optimisation results but replaces forecasted scenario data with realised conditions for demand, renewable generation, and forced outages. Unit commitments from the DA-UCED remain fixed, as do reserve allocations, depending on how much of the reserves are made available in this market phase. Generators committed in the DA-UCED are locked for a configurable set of technologies, ensuring dispatch flexibility while preserving unit status. Additionally, reserves allocated in the DA-UCED might be partially or fully restricted in the ID-ED to guarantee their availability for balancing purposes outside of market dispatch. Similarly, DSR dispatch from DA-UCED is partially fixed in ID-ED to reflect that certain demand segments only respond to day-ahead price signals or require advance activation times that preclude intraday participation. The configurable fractions α^{exDSR} and α^{imDSR} determine what portion of the day-ahead DSR dispatch is locked in the intraday market, with the remaining portion free to respond to intraday price signals.

To ensure continuity across the target year, boundary conditions for generators, storage units, and DSR components are carried forward from one rolling horizon ($ro \in RO$) to the next. To reduce computational complexity and enable parallelised market simulations, a streamlined approach is

adopted: DA-UCED results from one rolling horizon are passed to the next, and ID-ED results are similarly transferred between consecutive rolling horizons. This approach balances computational efficiency with consistency in market outcomes.

The entire rolling horizon calculation process is mathematically summarised below:

- From DA-UCED of rolling horizon *ro* to ID-ED of same rolling horizon *ro*:
  - Unit commitments from DA-UCED are respected in ID-ED:

$$u_{n,s,t}^{\mathrm{ID,ro}} = u_{n,s,t}^{\mathrm{DA,ro}} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{UC}} \tag{9.5}$$

  - Reserves allocated in DA-UCED are blocked in ID-ED with the static method as shown below(fraction β^i):

$$r_{n,s,t}^{i,j,\mathrm{ID,ro}} = \beta^i r_{n,s,t}^{i,j,\mathrm{DA,ro}} \quad \forall t \in T, \forall n \in N, \forall i \in I, \forall j \in \{+,-\}, \forall s \in S^{\mathrm{store},i,j} \cup S^{\mathrm{gen},i,j} \tag{9.6}$$

  - Reserves allocated in DA-UCED are blocked in ID-ED with the dynamic imbalance method (available for FRR only). Blocking fractions $\beta_{n,t}^{\mathrm{FRR},j}$ are computed per bus and per snapshot based on forecast errors (as defined in equation 13.16). Equation (9.7) and (9.8) can for example represent a situation where forecast error >0 (so demand has been underestimated or generation overestimated). To compensate for this forecast error, the use of FRR in ID is allowed only in the upward direction, proportionally up to the magnitude of the forecast error. No use of FRR down is permitted in this case. The converse is true in the case of negative forecast errors, such that no use of up reserves is allowed, and downward FRR can be used proportionally up to the magnitude of the forecast error.

$$\beta_{n,t}^{\mathrm{FRR},+} = \min\left(1, \max\left(0, 1 - \frac{FE_{n,t}}{\sum_s r_{n,s,t}^{\mathrm{FRR},+}}\right)\right) \quad \forall t \in T, \forall n \in N \tag{9.7}$$

$$\beta_{n,t}^{\mathrm{FRR},-} = \min\left(1, \max\left(0, 1 + \frac{FE_{n,t}}{\sum_s r_{n,s,t}^{\mathrm{FRR},-}}\right)\right) \quad \forall t \in T, \forall n \in N \tag{9.8}$$

  - Blocking fractions reduce intraday dispatch limits for generators and storage units where $\tilde{g}_{n,s,t}^{\max}$ and $\tilde{g}_{n,s,t}^{\min}$ are the modified per-unit limits for generators, $\tilde{h}_{n,s,t}^{\max}$ and $\tilde{h}_{n,s,t}^{\min}$ are the modified dispatch limits for storage units, and $\beta_{n,t}^{i,j}$ represents either the static or dynamic blocking fraction for reserve type i and direction j. The ramp limits are then adjusted accordingly, given the corresponding updates to the dispatch limits for generators, as defined in Equations (5.12) - (5.15).

$$\tilde{g}_{n,s,t}^{\max} = g_{n,s,t}^{\max} - \frac{\sum_{i \in I} \beta_{n,t}^{i,j} \cdot r_{n,s,t}^{i,+}}{\overline{g}_{n,s}} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{gen}}, \forall i \in I \tag{9.9}$$

$$\tilde{g}_{n,s,t}^{\min} = g_{n,s,t}^{\min} + \frac{\sum_{i \in I} \beta_{n,t}^{i,j} \cdot r_{n,s,t}^{i,-}}{\overline{g}_{n,s}} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{gen}}, \forall i \in I \tag{9.10}$$

$$\tilde{h}_{n,s,t}^{\max} = h_{n,s,t}^{\max} - \sum_{i \in I} \beta_{n,t}^{i,j} \cdot r_{n,s,t}^{i,+} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{store}} \tag{9.11}$$

$$\tilde{h}^{\min}_{n,s,t} = h^{\min}_{n,s,t} + \sum_{i \in I} \beta^{i,j}_{n,t} \cdot r^{i,-}_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store}} \tag{9.12}$$

- Explicit DSR dispatch from DA-UCED is partially fixed in ID-ED (fraction α^{exDSR}):

$$g^{\max,\text{ID}}_{n,s,t} = g^{\max}_{n,s,t} - \alpha^{\text{exDSR}} \left(g^{\max}_{n,s,t} - \frac{g^{\text{DA,ro}}_{n,s,t}}{\overline{g}_{n,s}} \right) \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{exDSR}} \tag{9.13}$$

$$g^{\min,\text{ID}}_{n,s,t} = \alpha^{\text{exDSR}} \frac{g^{\text{DA,ro}}_{n,s,t}}{\overline{g}_{n,s}} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{exDSR}} \tag{9.14}$$

These equations lock in a fraction α^{exDSR} of the day-ahead dispatch while removing the same fraction from the unused capacity, reflecting that explicit DSR providers who were activated in DA remain committed in ID, while those who were not activated cannot fully participate in ID.

- Implicit DSR dispatch from DA-UCED is partially fixed in ID-ED (fraction α^{imDSR}):

$$h^{\max,\text{ID}}_{n,s,t} = h^{\max}_{n,s,t} - \alpha^{\text{imDSR}} \left(h^{\max}_{n,s,t} - \frac{h^{\text{DA,ro}}_{n,s,t}}{\overline{h}_{n,s}} \right) \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{imDSR}} \tag{9.15}$$

$$h^{\min,\text{ID}}_{n,s,t} = h^{\min}_{n,s,t} + \alpha^{\text{imDSR}} \left(-h^{\min}_{n,s,t} + \frac{m^{\text{DA,ro}}_{n,s,t}}{\overline{h}_{n,s}} \right) \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{imDSR}} \tag{9.16}$$

$$h_{n,s,t} \geq \alpha^{\text{imDSR}} \cdot h^{\text{DA,ro}}_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{imDSR}} \tag{9.17}$$

$$m_{n,s,t} \geq \alpha^{\text{imDSR}} m^{\text{DA,ro}}_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{imDSR}} \tag{9.18}$$

where $h^{\text{DA,ro}}_{n,s,t}$ represents the dispatch (discharge) and $m^{\text{DA,ro}}_{n,s,t}$ represents the store (charge) from the day-ahead market for implicit DSR storage units. Equations (9.15) and (9.16) reduce available flexibility in ID by fixing a fraction of what was dispatched/charged in DA while maintaining the energy balance constraints defined in equation (4.1). Equations (9.17) and (9.18) ensure that the intra-day dispatch or store are bounded by the day-ahead results, aligning both market timeframes results.

- From DA-UCED of rolling horizon *ro* to DA-UCED of rolling horizon *ro+1*, the boundary conditions are updated as:

  - Initial dispatch of *ro+1* is set as dispatch of *ro* at time *T'*:

$$g^{\text{DA,ro+1}}_{n,s,0} = g^{\text{DA,ro}}_{n,s,T'} \quad \forall n \in N, \forall s \in S^{\text{gen}} \cup S^{\text{exDSR}} \cup S^{\text{lolDSR}} \tag{9.17}$$

  - Initial state-of-charge *ro+1* is set as state-of-charge of *ro* at time *T'*:

$$soc^{\text{DA,ro+1}}_{n,s,0} = soc^{\text{DA,ro}}_{n,s,T'} \quad \forall n \in N, \forall s \in S^{\text{store}} \cup S^{\text{imDSR}} \tag{9.19}$$

  - Initial committable statuses of *ro+1* are set as on following the final statuses of *ro* at time $T' - T^{\min,\text{up}}_{s,n}$, to respect equation (2.3). This is performed iteratively from one rolling horizon to the next. For instance, if $u^{\text{DA,ro}}_{n,s,T'} = u^{\text{DA,ro}}_{n,s,T'-1} = 1$, $u^{\text{DA,ro}}_{n,s,T'-2} = 0$, and $T^{\min,\text{up}}_{s,n} = 5$, then the generator must be on for the first 3 time steps of *ro+1*, $u^{\text{DA,ro+1}}_{n,s,1} = u^{\text{DA,ro+1}}_{n,s,2} = u^{\text{DA,ro+1}}_{n,s,3} = 1$.

- Initial committable statuses of *ro+1* are set as off following the final statuses of *ro* at time $T' - T_{s,n}^{\min,\text{down}}$, to respect equation (2.4). This is performed iteratively from one rolling horizon to the next. For instance, if $u_{n,s,T'}^{\text{DA,ro}} = u_{n,s,T'-1}^{\text{DA,ro}} = 0, u_{n,s,T'-2}^{\text{DA,ro}} = 1$, and $T_{s,n}^{\min,\text{down}} = 4$, then the generator must be off for the first 2 time steps of *ro+1*, $u_{n,s,1}^{\text{DA,ro+1}} = u_{n,s,2}^{\text{DA,ro+1}} = 0$.

- From ID-ED of rolling horizon *ro* to ID-ED of rolling horizon *ro+1*, the boundary conditions are updated as:

  - Initial dispatch of *ro+1* is set as dispatch of *ro* at time *T'*:

$$g_{n,s,0}^{\text{ID,ro+1}} = g_{n,s,T'}^{\text{ID,ro}} \quad \forall n \in N, \forall s \in S^{\text{gen}} \cup S^{\text{exDSR}} \cup S^{\text{lolDSR}} \tag{9.20}$$

  - Initial state-of-charge *ro+1* is set as state-of-charge of *ro* at time *T'*:

$$soc_{n,s,0}^{\text{ID,ro+1}} = soc_{n,s,T'}^{\text{ID,ro}} \quad \forall n \in N, \forall s \in S^{\text{store}} \cup S^{\text{imDSR}} \tag{9.21}$$

This structured implementation process establishes a seamless link between DA-UCED and ID-ED, effectively mitigating the impact of forecast uncertainty while ensuring economic efficiency, operational security, and system reliability. Additionally, it reduces computational burden by enabling the parallelisation of DA and ID runs, and eliminating the need to run the DA market for every ID outage scenario.

3.4. Capacity expansion

3.4.1. Price cap update

3.4.1.1. Background

Price caps are regulatory mechanisms that set maximum clearing prices in electricity markets to protect consumers from extreme price volatility while ensuring market efficiency. These caps are typically implemented as the Value of Lost Load (VoLL), representing the maximum willingness of consumers to pay for electricity before accepting supply shortages. In the European context, ACER has established the Harmonised Maximum Market Clearing Price (HMMCP) methodology to ensure consistent price cap treatment across member states.

Price caps significantly influence market outcomes and investment decisions. When markets approach scarcity conditions, prices can spike towards the cap, affecting both short-term dispatch decisions and long-term capacity investment signals. Static price caps may undervalue reliability or create investment shortfalls, while adaptive mechanisms can better reflect evolving market conditions and consumer preferences over time.

The dynamic updating of price caps based on market conditions is essential for maintaining market efficiency while providing appropriate investment signals. The HMMCP methodology allows for systematic increases in price caps when specific market stress conditions are observed,

ensuring that caps remain aligned with actual market conditions and consumer valuation of reliability.

3.4.1.2. Target

The price cap update mechanism aims to implement ACER's HMMCP methodology[47] within the EVA framework to ensure realistic representation of evolving price caps across European electricity markets. The system provides adaptive price cap adjustments that respond to market stress events, ensuring that:

- Price caps appropriately reflect market scarcity conditions and consumer willingness to pay for reliability
- Investment signals remain economically viable by allowing adequate revenue recovery during stress periods
- Market outcomes align with regulatory frameworks established by ACER across EU member states
- Price cap evolution is tracked transparently throughout EVA iterations to support convergence analysis

The mechanism integrates seamlessly with NPV calculations by providing dynamic price ceiling constraints that affect revenue calculations, ensuring that investment decisions reflect realistic market price limitations while accounting for their potential evolution over time.

3.4.1.3. Implementation strategy

The price cap update mechanism is implemented as a post-processing function, which processes market clearing results from both day-ahead and intraday optimisations to detect price stress events and adjust caps accordingly.

The implementation follows ACER's HMMCP methodology with the following key components:

1. **Event Detection**: The system monitors when marginal prices exceed 70% of the original harmonised maximum clearing price in at least 2 market time units across at least 2 different days within a 30-day rolling window. Events are detected globally across all bidding zones rather than per individual zone; if the condition is met in any bidding zone, the event is triggered simultaneously across all zones, ensuring harmonised application/price caps across member states.
2. **Transition Period Management**: After an event is detected, a 28-day transition period applies where prices are capped at the pre-event value. Additional events during transition periods are not counted and do not generate extra price increases, ensuring market stability during adjustment phases.

3. **Price Cap Adjustment**: When transition periods end, pending events trigger price cap increases by the configured increment amount (typically 500 EUR/MWh), up to the maximum allowable cap. The updated caps apply to both day-ahead and intraday markets, in both energy and reserves prices.

4. **Multi-Year Handling**: Price caps evolve across target years using configurable interpolation methods to ensure a consistent progression throughout the modelling horizon. Users can select among four options:

    - Linear interpolation: Gradually adjusts price caps between known target years based on each climate year's individual event history. Each climate year follows its own trajectory.
    - Repeat last year: Keeps the last available (final) value constant until the next defined target year. Produces stepwise transitions with each climate year maintaining its own final cap.
    - Do not interpolate: Uses only explicitly defined target years without adjustment. Produces discrete jumps between years with all climate years starting identically.
    - Expected price cap (expected): Uses the expected (mean) final price cap across all climate years from the previous target year. All climate years start from the same baseline in the next target year, reflecting expected behaviour across all scenarios.*

The example below illustrates the different methods for a scenario with 3 climate years (CY1, CY2, CY3) having different event counts in TY 2026:

TY 2026 Results (all methods other than `expected` identical for first target year):

Climate Year	Events	Initial Cap (€/MWh)	Final Cap (€/MWh)
CY1	1	4,500	5,000
CY2	5	4,500	7,000
CY3	2	4,500	5,500
Expected (Mean)	**2.67**	**—**	**5,833**

TY 2030 Starting Price Cap (methods differ):

Climate Year	Linear Interpolation	Repeat Last Year	Do Not Interpolate	Expected Price Cap
CY1	6,500	5,000	5,000	9,838
CY2	14,500	7,000	5,000	9,838
CY3	8,500	5,500	5,000	9,838

Notes:

- If the interpolated/expected final cap is lower than the configured initial cap for the next year, the "initial cap of the next year" takes precedence to maintain consistency.
- The "Linear Interpolation" calculation for TY 2030: `(2030-2026-1) × 500 × events + final_cap_2026`
- The "Expected Price Cap" calculation for TY 2030: `(2030-2026-1) × 500 × expected_events + expected_final_cap_2026` where `expected_events = (1+5+2)/3 = 2.67` and `expected_final_cap_2026 = (5,000+7,000+5,500)/3 = 5,833` → `3 × 500 × 2.67 + 5,833 = 9,838 EUR/MWh`
- The "Expected Price Cap" method uses interpolation based on the mean events and mean final cap across all climate years, providing the same starting value (9,838 EUR/MWh) for all climate years and delivering more stable and consistent results across stochastic scenarios.

The mechanism generates comprehensive tracking outputs including timeseries of price cap evolution, comparison plots of marginal prices across iterations, and detailed logging of event detection and cap adjustments. These outputs support convergence monitoring and provide transparency into how price caps evolve throughout the EVA process.

The plot below represents the implemented methodology.

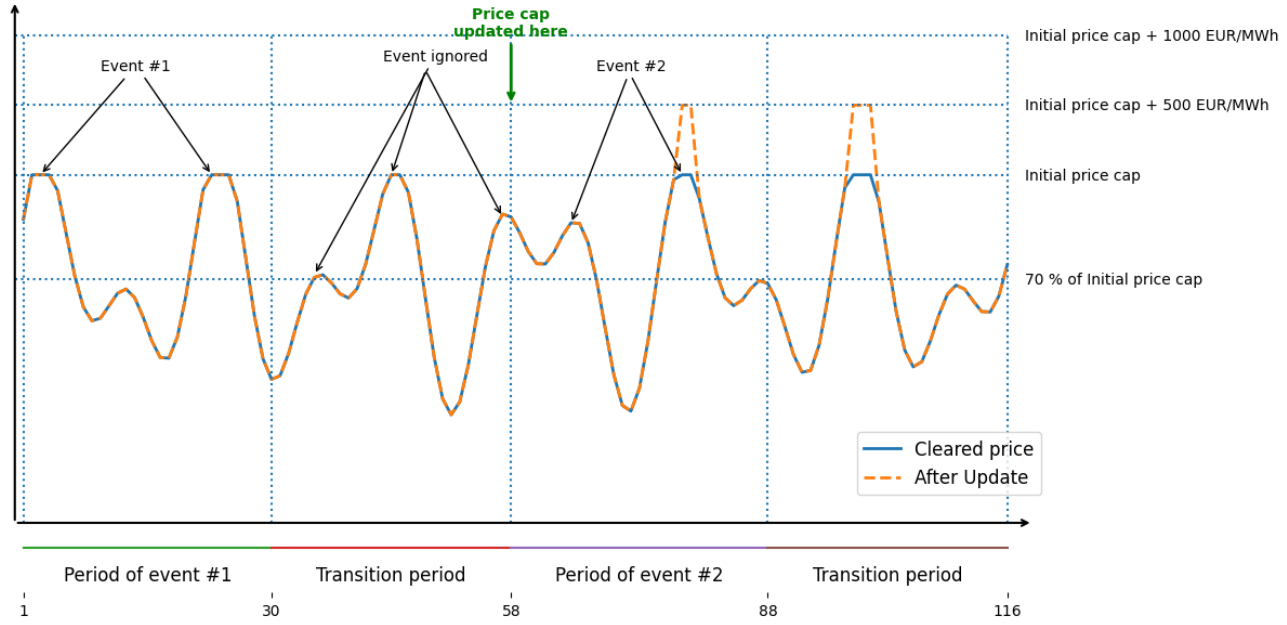


Figure 7: Visual representation of the HMMCP methodology.

3.4.2. Net present value calculations

3.4.2.1. Background

The net present value (NPV) calculation is essential for determining the economic viability of power assets in the electricity market. It encompasses multiple income sources including day-ahead markets, real-time operations, balancing services, and exogenous sources of revenues. It also considers the multiple costs incurred by the assets, such operational costs, fixed costs, and capital costs. This comprehensive approach ensures that all potential revenue and cost streams are considered when evaluating investment decisions and capacity adjustments.

3.4.2.2. Target

The net present value (NPV) calculation framework aims to establish a comprehensive system for evaluating the financial performance of power assets (generation, storage, DSR). It ensures accurate accounting of revenue streams by integrating income from energy markets, reserve provisions, and exogenous sources[23] into a unified calculation framework. It also accounts for accurate calculations of costs based on the market outcomes. The system enables detailed profitability assessment through NPV per MW calculations, which serve as key indicators for investment decisions. This metric is particularly valuable as it corresponds to the shadow price of capacity constraints and forms the basis for the gradient descent optimisation approach detailed in the Capacity Update Section Capacity update. Furthermore, the framework supports the achievement of market equilibrium through an iterative process where capacity adjustments are made based on profitability indicators, ensuring a balanced approach to investment and decommission decisions.

3.4.2.3. Implementation strategy

As a result of the DA-UCED and ID-ED optimisation, the model contains all required information to post-calculate the total revenue per market participant occurring in one Monte Carlo scenario ($sy \in SY$) and for one target year ($ty \in TY$). The relevant quantities are the generation profiles of generators and storage facilities, which are a direct solution of the optimisation, as well as the market prices, which result from the shadow price of the nodal balance constraint[24]. Exogenous time series of revenues and other costs can also be added to better account for the profitability of the market participants.

The net present value (NPV) calculation framework follows a multi-component approach, where individual revenue and cost streams are computed separately before being aggregated into a comprehensive NPV assessment. Total revenues and costs are calculated for each scenario (*sy*) and target year (*ty*) by summing the results of all rolling horizons within the ty[25]. The final NPV calculation consolidates the outcomes across multiple SYs and TYs, yielding a single representative value per *ty*.

The aggregation over climate years uses the probabilities PR_{cy} defined in the notation table. By default, all climate years are weighted equally ($PR_{\text{cy}} = 1/|CY|$). Optionally, user-specified weights can be assigned to each climate year, enabling a weighted average that emphasises specific historical weather conditions.

The aggregation over sample years PR_{sy}, which is the cartesian product of climate years and outage scenarios as defined in Eq. (8.1), is used for NPV calculations in Eq. (11.8) below.

To simplify the equations below, consider $g^{\text{DA}}_{n,s,t}/g^{\text{ID}}_{n,s,t}$ as the dispatch of the asset in the day-ahead/intraday markets if s is a generator or an explicit DSR component, or as the net dispatch (i.e., $g^{\text{DA}}_{n,s,t} = h^{\text{DA}}_{n,s,t} - m^{\text{DA}}_{n,s,t}$ and $g^{\text{ID}}_{n,s,t} = h^{\text{ID}}_{n,s,t} - m^{\text{ID}}_{n,s,t}$), of the asset in the day-ahead/intraday markets if s is a storage unit or an implicit DSR component.

1. Day-ahead Energy Market Revenue Calculation:

$$Revenue^{\text{DA}}_{n,s} = \sum_{t} \left(\lambda^{\text{DA}}_{n,t} g^{\text{DA}}_{n,s,t} + ER^{\text{DA}}_{n,s,t}\right) \quad \forall n \in N, \forall s \in S^{\text{EVA}} \tag{11.1}$$

   which takes into account the revenue from the dispatch of the asset ($g^{\text{DA}}_{n,s,t}$) times the day-ahead market price at its bidding zone ($\lambda^{\text{DA}}_{n,t}$)[26], as well as any other day-ahead exogenous revenue streams that can be allocated to the generator ($ER^{\text{DA}}_{n,s,t}$).

2. Intra-day Energy Market Revenue Calculation:

$$Revenue^{\text{ID}}_{n,s} = \sum_{t} \lambda^{\text{ID}}_{n,t} \left(g^{\text{ID}}_{n,s,t} - g^{\text{DA}}_{n,s,t}\right) + ER^{\text{ID}}_{n,s,t} \quad \forall n \in N, \forall s \in S^{\text{EVA}} \tag{11.2}$$

   which takes into account the revenue from the adjustment of the asset's position ($g^{\text{ID}}_{n,s,t} - g^{\text{DA}}_{n,s,t}$) times the intra-day market price at its bidding zone ($\lambda^{\text{ID}}_{n,t}$), as well as any other intra-day exogenous revenue streams that can be allocated to the generator ($ER^{\text{ID}}_{n,s,t}$).

3. Reserve Market Revenue Calculation:

$$Revenue^{\text{rsv}}_{n,s} = \sum_{t} \sum_{i} \sum_{j} \lambda^{i,j}_{n,t} r^{i,j}_{n,s,t} \quad \forall n \in N, \forall s \in S^{\text{EVA}} \tag{11.3}$$

   which takes into account the revenue from reserving the asset ($r^{i,j}_{n,s,t}$) times the reservation price ($\lambda^{i,j}_{n,t}$). Notice that it accounts for revenues in all reserve markets $i \in I$ and in all directions $j \in \{+, -\}$.

4. Commitment Cost Calculation:

$$Cost^{\text{DA}}_{n,s} = \sum_{t} \left(suc^{\text{DA}}_{n,s,t} + sdc^{\text{DA}}_{n,s,t}\right) \quad \forall n \in N, \forall s \in S^{\text{UC,fixed}} \tag{11.4}$$

   which takes into account the costs from start-up ($suc^{\text{DA}}_{n,s,t}$) and shut-down ($sdc^{\text{DA}}_{n,s,t}$) for committable generators whose commitment is **fixed** in the intra-day market ($s \in S^{\text{UC,fixed}}$). For these generators, the DA commitment is the realised one, so their start-up and shut-down costs are fully accounted for through the DA network. Generators that are **free** to recommit in ID

($s \in S^{\text{UC,free}}$, configured via `id_free_commitment_carriers`) are excluded from this term to avoid double-counting.

5. Energy and Commitment Cost Calculation (Intra-day):

$$Cost^{\text{ID}}_{n,s} = \sum_t MC_{n,s,t} g^{\text{ID}}_{n,s,t} + \sum_t \left(suc^{\text{ID}}_{n,s,t} + sdc^{\text{ID}}_{n,s,t} \right) \quad \forall n \in N, \forall s \in S^{\text{EVA}} \tag{11.5}$$

which takes into account the costs from the dispatch of the asset in the intra-day market ($g^{\text{ID}}_{n,s,t}$) times its marginal cost ($MC_{n,s,t}$). For generators free to recommit in ID ($s \in S^{\text{UC,free}}$), the start-up and shut-down costs from the ID network ($suc^{\text{ID}}_{n,s,t}$, $sdc^{\text{ID}}_{n,s,t}$) are also included, as ID represents their realised commitment. For generators fixed in ID ($s \in S^{\text{UC,fixed}}$), the start-up and shut-down terms are zero in this equation (costs are already captured in Eq. (11.4)).

6. Other Costs Calculation:

$$Cost^{\text{other}}_{n,s} = \sum_t \left(FC_{n,s,t} + MTC_{n,s,t} \right) \quad \forall n \in N, \forall s \in S^{\text{EVA}} \tag{11.6}$$

which takes into account other costs of the asset, such as fixed costs ($FC_{n,s,t}$) and maintenance costs ($MTC_{n,s,t}$). These can be replaced by the annuity calculation in point 8. below.

7. Total profit calculation:

$$\begin{aligned} Profit_{n,s} = {} & Revenue^{\text{DA}}_{n,s} + Revenue^{\text{ID}}_{n,s} + Revenue^{\text{rsv}}_{n,s} \\ & - Cost^{\text{DA}}_{n,s} - Cost^{\text{ID}}_{n,s} - Cost^{\text{other}}_{n,s} \end{aligned} \quad \forall n \in N, \forall s \in S^{\text{EVA}} \tag{11.7}$$

Steps 1-7 determine the profit for a given *ty* and *sy*, resulting in $Profit^{\text{sy,ty}}_{n,s}$.[27] Additionally, $Annuity^{\text{sy,ty}}_{n,s}$ represents the annuity of generator *s* in bidding zone *n*, accounting for capital costs, interest, and depreciation. This value can also be given per *ty* and *sy*.

8. Annuity Calculation Following ERAA Methodology:

Following the ERAA methodology, the annuity calculation incorporates investors' risk aversion by applying a hurdle rate that combines the Weighted Average Cost of Capital (WACC) with a hurdle premium. The hurdle rate is defined as:

$$HurdleRate_{n,s} = WACC_{n,s} + HurdlePremium_{n,s}$$

The annuity of CAPEX is then calculated using the hurdle rate:

$$Annuity^{\text{CAPEX}}_{n,s} = CAPEX_{n,s} \times \frac{HurdleRate_{n,s}}{1 - \left(\frac{1}{1 + HurdleRate_{n,s}} \right)^{\text{LT}_{n,s}}}$$

The hurdle rate also adjusts the Fixed Operation and Maintenance (FOM) costs. As FOM is a yearly cost, the annuity of FOM is calculated assuming a one-year lifetime:

$$Annuity^{\text{FOM}}_{n,s} = FOM_{n,s} \times (1 + HurdleRate_{n,s})$$

The total annuity is the sum of both components:

$$Annuity_{n,s}^{\mathrm{sy,ty}} = Annuity_{n,s}^{\mathrm{CAPEX}} + Annuity_{n,s}^{\mathrm{FOM}}$$

where:

- $CAPEX_{n,s}$ is the capital expenditure per unit capacity (€/MW)
- $FOM_{n,s}$ is the fixed operation and maintenance cost per unit capacity (€/MW/year)
- $LT_{n,s}$ is the economic lifetime of the asset in years
- $WACC_{n,s}$ is the Weighted Average Cost of Capital for the technology
- $HurdlePremium_{n,s}$ is the technology-specific risk premium

The hurdle premium compensates for the deviation of actual returns from expected returns, accounting for revenue distribution volatility, downside risk, model risk, and policy risk. This framework ensures that investment in new or existing capacity is economically viable when the expected return exceeds the hurdle rate.

> Note: for existing capacity (i.e., assets not subject to new investments, just to decommissioning, mothballing, or lifetime extension), the CAPEX is set to zero.

9. Interpolation to non-simulated years:

Since not all years of the assets' lifetime are explicitly simulated, calculating the NPV for a given ty requires projecting both $Profit_{n,s}^{\mathrm{sy,ty'}}$ and $Annuity_{n,s}^{\mathrm{sy,ty'}}$ over the entire lifetime of the asset ($ty' \in [ty, ty+1, ..., LT_{n,s}]$). Before projecting, the profits and annuities of each simulated target year are divided by the asset's installed capacity in that target year, $\overline{g}_{n,s}^{\mathrm{ty}}$, and the projections below are applied to these values per MW. Simulated target years in which the asset has no installed capacity take their values per MW from the neighbouring simulated target years. This projection can be performed using one of the following three approaches:

a) **Interpolation between simulated target years**: Profits and annuities are interpolated between simulated target years. For instance, if *ty'* falls between two simulated target years (ty_1 and ty_2), such as $ty_1 \leq ty' \leq ty_2$, the profit for *ty'* is calculated as: $Profit_{n,s}^{\mathrm{sy,ty'}} = Profit_{n,s}^{\mathrm{sy,ty_1}} + \frac{ty'-ty_1}{ty_2-ty_1}\left(Profit_{n,s}^{\mathrm{sy,ty_2}} - Profit_{n,s}^{\mathrm{sy,ty_1}}\right)$. The annuity follows the same equation (replacing Profit with Annuity).

b) **Constant extension from the last simulated target year**: Profits and annuities remain equal to the values of the most recent simulated target year. For the same example in approach a), the projection is $Profit_{n,s}^{\mathrm{sy,ty'}} = Profit_{n,s}^{\mathrm{sy,ty_1}}, Annuity_{n,s}^{\mathrm{sy,ty'}} = Annuity_{n,s}^{\mathrm{sy,ty_1}}$

c) **Assignment to the closest simulated target year:** Profits and annuities are assigned based on the closest simulated target year. For the same example in approach a), * If $ty' - ty_1 \leq ty_2 - ty'$ then $Profit_{n,s}^{\mathrm{sy,ty'}} = Profit_{n,s}^{\mathrm{sy,ty_1}}, Annuity_{n,s}^{\mathrm{sy,ty'}} = Annuity_{n,s}^{\mathrm{sy,ty_1}}$ * Otherwise $Profit_{n,s}^{\mathrm{sy,ty'}} = Profit_{n,s}^{\mathrm{sy,ty_2}}, Annuity_{n,s}^{\mathrm{sy,ty'}} = Annuity_{n,s}^{\mathrm{sy,ty_2}}$.

The EU-Flex model uses approach a) between simulated target years and approach b) beyond the last simulated target year (before the first simulated target year, the values of the first one are held constant). Approach c) is not implemented. This results in a vector of profits and annuities for each asset s in bidding zone n for each scenario sy, spanning all years of the asset's lifetime. These vectors serve as inputs for the subsequent calculation of the NPV.

10. Comprehensive NPV[28] Calculation:

$$NPV_{n,s}^{\mathrm{ty}} = \sum_{\mathrm{ty}'=\mathrm{ty}}^{\mathrm{LT}_{n,s}} \frac{\sum_{\mathrm{sy}} \left(Profit_{n,s}^{\mathrm{sy},\mathrm{ty}'} - Annuity_{n,s}^{\mathrm{sy},\mathrm{ty}'} \right) PR_{\mathrm{sy}}}{\overline{g}_{n,s}^{\mathrm{ty}'}} (1+\gamma)^{(\mathrm{today}-\mathrm{ty}')} \quad \forall n \in N, \forall s \in S^{\mathrm{EVA}} \qquad (11.8)$$

which calculates the NPV of each asset per simulated target year (*ty*), where $\overline{g}_{n,s}^{\mathrm{ty}'}$ is the installed capacity of the asset in year *ty'*; for non-simulated years, the fraction is the projected profit per MW from step 9. Because profits are divided by the capacity of the same year, the result is the value of one MW that is present from *ty* until the end of the asset's lifetime, and capacity changes in later target years do not distort the NPV at *ty*. Note that $\overline{g}_{n,s}^{\mathrm{ty}'} = \overline{h}_{n,s}^{\mathrm{ty}'}$ if s is a storage or implicit DSR component.

Discount Rate Implementation - Extension to NPV Calculation:

Building upon the ERAA methodology for annuity calculation, the EU-Flex model extends the use of technology-specific hurdle rates to the NPV discounting process. This ensures methodological consistency throughout the economic evaluation workflow. The discount rate γ in Equation (11.8) can be configured in two ways:

1. **Technology-specific hurdle rates (default)**: When `use_hurdle_rates` is enabled (default), the model uses technology-specific hurdle rates calculated as $\gamma_{n,s} = WACC_{n,s} + HurdlePremium_{n,s}$ for each asset. This approach extends the ERAA methodology by applying the same hurdle rate consistently for:
   - **Annuity calculation**: Used in the capital recovery factor (CRF) and FOM adjustment as described in step 7
   - **NPV discounting**: Used in Equation (11.8) to discount future cash flows

   This dual application ensures that the same risk-adjusted discount rate is used throughout the investment evaluation process. If hurdle rate data (WACC or Hurdle_Premium) is unavailable or invalid for a specific asset, the system falls back to the global `discount_rate` parameter.
2. **Global discount rate**: When `use_hurdle_rates` is disabled, a single global discount rate is applied to all assets for both annuity calculation and NPV discounting, regardless of technology type. This mode can be useful for sensitivity analysis or simplified scenarios where technology-specific risk premiums are not required.

The default configuration uses hurdle rates with a fallback discount rate of 5%. This can be controlled via the configuration parameters `costs.use_hurdle_rates` (boolean) and `costs.discount_rate` (float).

Rationale for Extension: While the ERAA methodology primarily uses hurdle rates for annuity calculations, the EU-Flex model extends this to NPV discounting to maintain consistency in risk adjustment across all financial calculations. This ensures that both the cost side (annuity) and the valuation side (NPV) reflect the same technology-specific risk profile, providing a more coherent economic signal for capacity investment decisions.

This hierarchical structure ensures that all revenue and cost streams are properly captured in the final NPV calculation. By evaluating these revenues across all target years and CYs, with appropriate weighting and discounting, the NPV equation determines the overall economic viability of the generation asset. **Figure 8** illustrates the NPV calculation in a multi-year context.

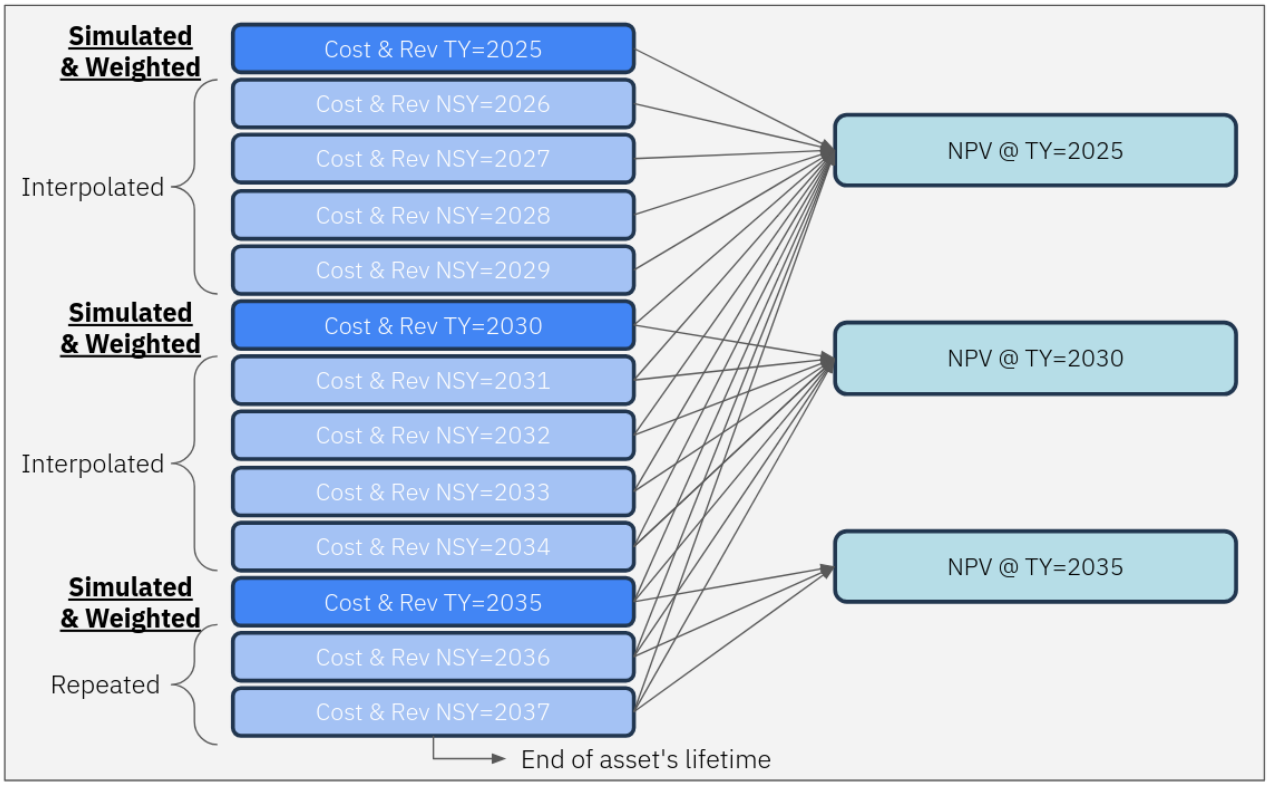


Figure 8: Illustration of the NPV calculation in a multi-year context.

3.4.3. Capacity update

3.4.3.1. Background

In liberalised electricity markets, generation capacity changes as investors decide whether to build, expand, or retire power plants based on expected financial returns. These decisions rely on simple economic principles:

- If revenues exceed total costs (including risk premium), investors are likely to expand capacity.
- If costs outweigh revenues, existing assets may be decommissioned or mothballed.

This market-driven adjustment process is crucial for maintaining system adequacy and economic efficiency. However, real-world investment decisions are more complex due to factors such as long lead times, market uncertainties, and policy constraints. For example:

- A company considering a new solar farm must evaluate installation costs, expected electricity prices, and potential subsidies before proceeding.
- An investor in a gas-fired power plant weighs fuel costs, carbon pricing, and operational flexibility to determine profitability.
- A nuclear plant operator may defer retirement if market conditions improve, ensuring continued reliability in the system.

3.4.3.2. Target

The capacity expansion module[31] captures these real-world investment dynamics. It evaluates the profitability of assets and adjusts capacities accordingly until reaching a market equilibrium–where viable assets recover their cost, and uneconomical plants exit the system. By systematically modelling these decisions, this module helps ensure that electricity markets evolve efficiently while maintaining system reliability. As such, this module aims to simulate this market-driven investment process by:

- Evaluating the profitability of different technologies across all bidding zones.
- Adjusting generation and storage capacities based on economic signals.
- Respecting technical and policy constraints on capacity changes.
- Accounting for policy-driven decisions on expanding/shrinking capacity.
- Reaching an equilibrium state where capacities align with economic signals.

The module implements a crucial part in the iterative process that continues until either market equilibrium is achieved or maximum iterations are reached. This approach allows for gradual capacity adjustments while maintaining system stability throughout the optimisation process.

3.4.3.3. Implementation strategy

Capacity update in the workflow

The capacity update module implements an economic optimisation framework built on NPV calculations, incorporating all revenues and costs from market participants across scenarios of different CYs and outage realisations. **Figure 9** shows how the outputs from the preceding core components of the modelling framework (the pre-optimisation, the market simulation, and the net present value calculations) feed into the capacity update. Specifically, the modelling components go through the following steps:

1. The pre-optimisation is conducted for each target year (ty) and scenario (sy) combination.

2. The results of each pre-optimisation are passed through to the DA-UCED and ID-ED markets, which are solved for each rolling horizon (*ro*) until the last rolling horizon is reached.

3. Once the markets are solved for all *ty*'s, the NPVs are calculated and used to determine the capacities updated. With the new capacities, step 2 is restarted. Alternatively, step 1 can be re-performed if pre-optimisation plans need to be updated. This process is repeated over the iterations (*it*) until a convergence (ε) or max number of iterations ($IT^{\max}$) is reached.

4. Once the workflow reaches convergence, the final NPVs and capacities for a single target year are determined.

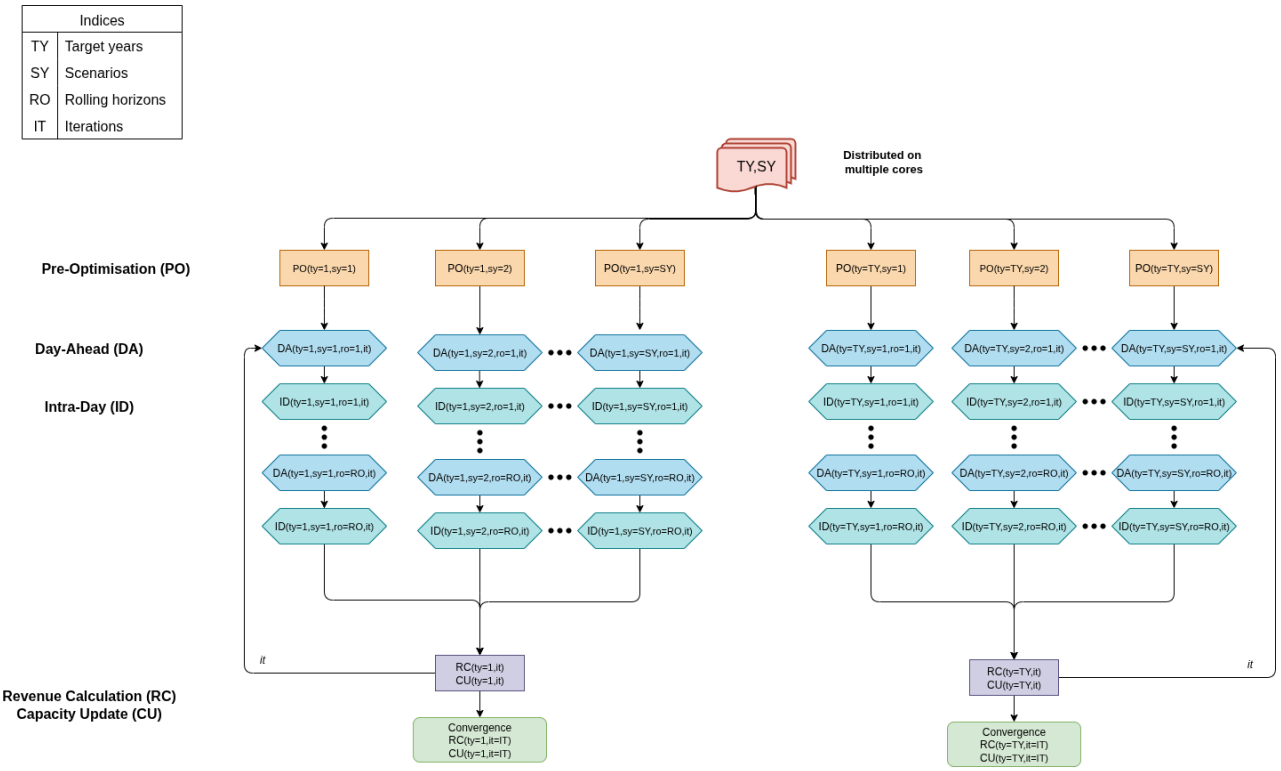


Figure 9: Visualisation of the EU-Flex workflow, showing how the core components are connected.

Moreover, the capacity update module explicitly includes policy or technical constraints for investments to represent the likely evolution of the EU energy system outside of market dynamics. These are based on minimum and maximum boundaries per technology type, enforceable at a TY resolution for each BZ, reducing the potential solution space for capacity updates.

General methodology

The capacity update follows a fixed step adjustment in each iteration:

$$\overline{g}_{n,s,\mathrm{it}+1} = \overline{g}_{n,s,\mathrm{it}} + \Delta g_{n,s} \frac{NPV_{n,s,\mathrm{it}}}{|NPV_{n,s,\mathrm{it}}|} \quad \forall n \in N, \forall s \in S^{\mathrm{EVA}} \tag{12.1}$$

in which the capacity is updated using a fixed step size $\Delta g_{n,s}$ (e.g., 50 MW increase or decrease), added or subtracted depending on whether an asset is profitable $NPV_{n,s,\mathrm{it}} > 0$ or not $NPV_{n,s,\mathrm{it}} < 0$. To ensure all expandable assets are evaluated in every iteration, a minimum capacity of 0.001 MW is always included to test viability. Additionally, configurable bounds are applied, as defined in equation (12.2) below, to ensure that capacity adjustments remain within both policy-driven and technical constraints.

$$\overline{g}_{\min,n,s} \leq \overline{g}_{n,s,\mathrm{it}} \leq \overline{g}_{\max,n,s} \quad \forall n \in N, \forall s \in S^{\mathrm{EVA}} \tag{12.2}$$

This approach follows a simpler heuristic-based update process while maintaining investment realism. Some additional steps are added to include other decisions, such as lifetime extension and mothballing. The following subsections detail how this capacity update mechanism operates for both existing and new assets, as well as how convergence is determined.

An optional **linear decay** of the step size is available to improve convergence stability. When enabled, the step size is linearly reduced from the base value $\Delta g_{n,s}^{\mathrm{base}}$ down to a configurable minimum $\Delta g_{n,s}^{\min}$ over a configurable number of decay iterations IT^{decay} (defaulting to the maximum number of iterations $IT^{\max}$ when not set). Once the decay period ends the step size remains at the minimum for all remaining iterations:

$$\Delta g_{n,s,\mathrm{it}} = \Delta g_{n,s}^{\mathrm{base}} \cdot \left(1 - \left(1 - \frac{\Delta g_{n,s}^{\min}}{\Delta g_{n,s}^{\mathrm{base}}}\right) \cdot \min\left(\frac{it}{IT^{\mathrm{decay}}}, 1\right)\right) \quad \forall n \in N, \forall s \in S^{\mathrm{EVA}} \tag{12.3}$$

The minimum step size $\Delta g_{n,s}^{\min}$ is an absolute value in MW. If it is not set, it defaults to 1% of the base step size.

Example: approach for existing assets

For existing assets, a negative NPV justifies disinvestment. Disinvestments are implemented in discrete steps: a fixed amount of capacity (e.g., 100 MW, as illustrated in the figure) is removed from the corresponding technology. Any capacity removed is carried forward to subsequent target years, ensuring continuity of the capacity update mechanism across target years. A small placeholder capacity (0.001 MW) is retained to preserve the possibility of future reinvestment, up to the starting installed capacity.

If the profitability signal reverses in subsequent iterations, the model may re-invest previously removed capacity, again in fixed steps. This allows the system to dynamically respond to changing economic conditions. Such reinvestment is only permitted when capacity does not increase from one target year to the next, thereby maintaining continuity and consistency of the capacity evolution across target years—i.e., for existing units, capacity should generally be decreasing over target years. This continuity constraint does not apply in the case of mothballing, as described below.

Mothballing

Mothballing allows existing assets to be temporarily taken offline rather than permanently decommissioned. This is relevant when an asset shows negative NPV in some target years but positive NPV in later target years—the asset can be temporarily removed and brought back online when market conditions improve.

The mothballing mechanism works as follows:

- When an existing asset has negative NPV in a target year, capacity is removed from that year and all subsequent years.
- If the asset later shows positive NPV in a future target year, the model evaluates whether to bring the capacity back online (demothball).
- To demothball, the **adjusted NPV** is calculated by adding the mothballing costs to the raw NPV. These costs include:
  - **Mothballing FOM** (€/kW/year): Fixed operation and maintenance cost during the mothballed period.
  - **Demothballing cost** (€/kW): One-time cost to bring the asset back online.
- Capacity is only reinstated if the adjusted NPV (including mothballing costs) remains positive and the capacity in the target year does not exceed the capacity of previous target years.

This approach ensures that bringing an asset back online is economically justified when accounting for the full cost of temporary retirement. For ERAA compliance, if an asset remains mothballed throughout the simulation without being demothballed, it is reported as `capacity_removed` in the final output.

Lifetime extension

Lifetime extension allows existing assets that reach the end of their technical lifetime to continue operating if economically viable. Following the ERAA approach, lifetime extension is only evaluated in the modelled target years that fall within or after the end of the original lifetime.

The lifetime extension mechanism works as follows:

- The model identifies target years that fall within the extension period (i.e., after the original commissioning year plus original lifetime).
- For these target years, the **adjusted NPV** is calculated to include the lifetime extension costs:
  - **Lifetime extension FOM** (€/kW/year): Additional maintenance costs required to keep an ageing asset operational during the extended period.
- If the adjusted NPV is positive, the asset's lifetime is extended by the configured extension period (e.g., 10 years), and capacity is set to match the previous target year.
- If the adjusted NPV is negative, capacity is set to 0.001 MW and the lifetime remains at its original value.
- If the end of lifetime falls between simulated target years, an additional NPV evaluation is performed for the extension period.
- For assets whose lifetime ends beyond the last modelled target year, an estimated NPV is calculated using the last modelled target year's NPV as a proxy for annual profit, discounted appropriately over the intervening years and adjusted for extension costs.

Both mothballing and lifetime extension can be enabled or disabled independently via the corresponding configuration parameters `eva.enable_mothballing and` eva.enable_lifetime_extension`. The full decision process for existing assets is illustrated in **Figure 10**.

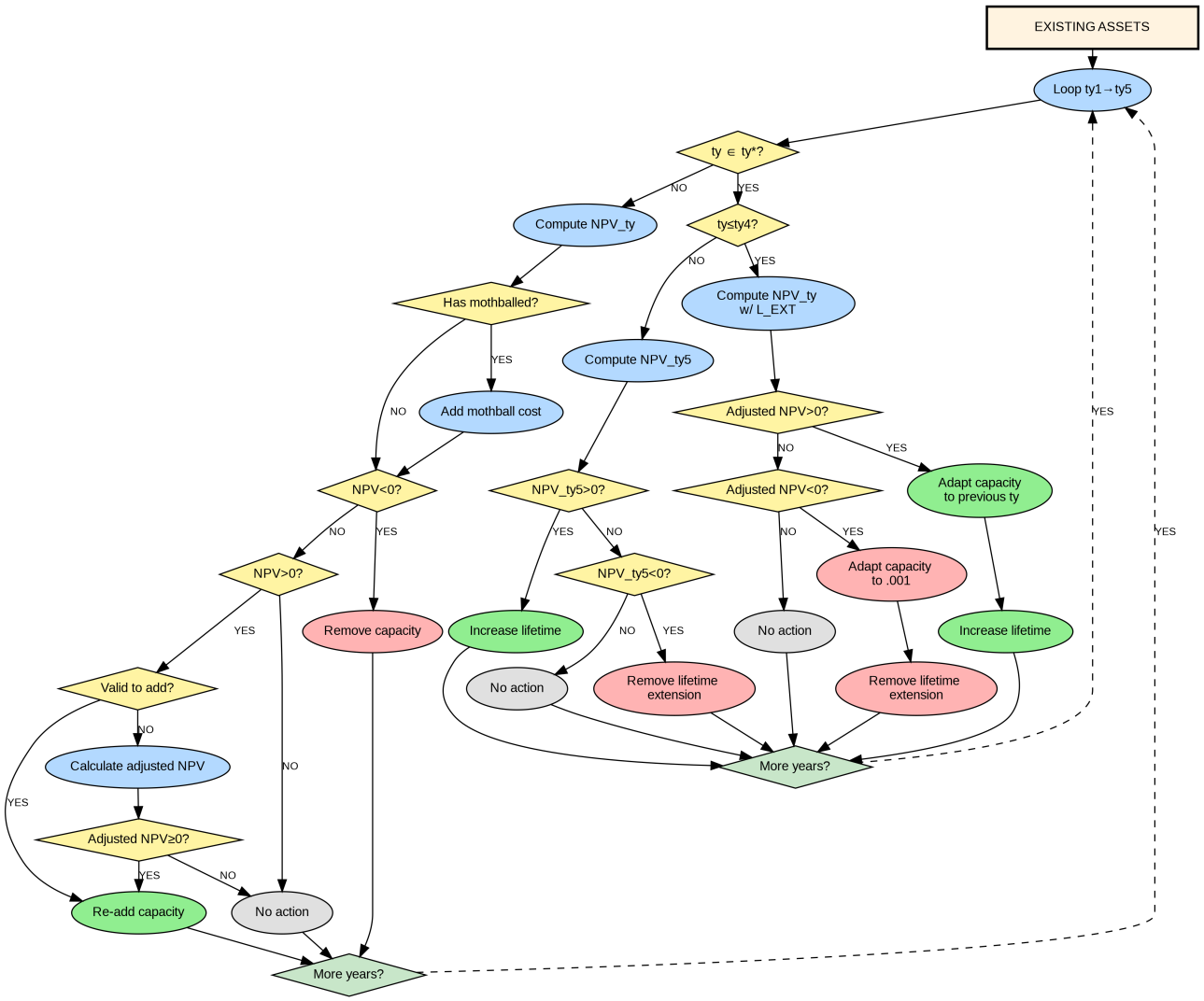


Figure 10: Decisions available for existing assets, based on their NPV for each potential strategy.

Example: approach for new assets

To enable potential expansion, a placeholder asset with an initial capacity of 0.001 MW is introduced for each eligible technology. This allows the simulation of the operation of expansion candidates in the DA and ID timeframes without significantly impacting the results. The capacity update process of new assets is shown in **Figure 11** below.

If a technology shows a positive NPV in a given target year, it remains active in all subsequent target year calculations. When the placeholder asset is consistently profitable across all simulated years, the model adds new capacity each year based on the defined update step. For instance, if the placeholder yields a positive investment signal in all target years, then the capacity is increased by a fixed amount, e.g., 100 MW. This is done cumulatively, building on previous additions. Conversely, if profitability is observed only in specific years, capacity is expanded only in those years, while still considering the previous cumulative additions.

If the profitability signal reverses in subsequent iterations, the model can also reduce previously added capacity in fixed steps, allowing the system to dynamically respond to changing economic conditions. Such capacity reductions are only permitted when capacity does not decrease from one target year to the next, thereby ensuring continuity and consistency of the capacity update mechanism across target years.

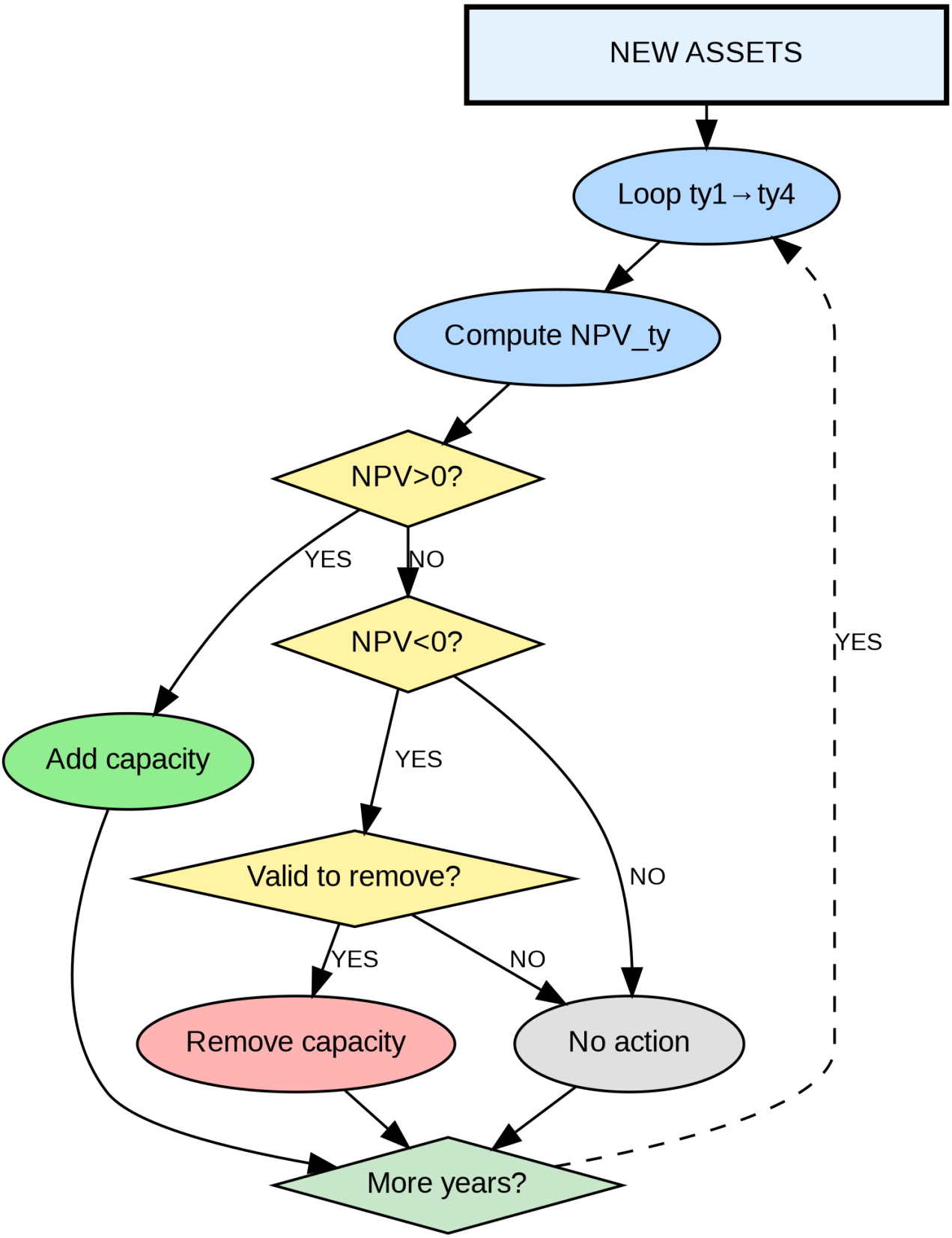


Figure 11: Investment into additional capacity.

Multi-iterations

This process of adding or removing capacity is adjusted dynamically based on updated NPVs in each iteration. In all cases (investment, decommissioning, mothballing and lifetime extension), minimum and maximum capacity limits can be defined for each asset to reflect system-level constraints, such as policy targets or regulatory limits. For example, maximum investment potentials can be considered which limit the commissioned capacities in a given zone, such as by limiting investments in gas power plants to a certain level or limiting demand side response levels to the maximum industrial/commercial potential.

Once the new capacities are calculated as described above, the process restarts. The DA and ID timeframes are re-simulated using the updated capacities, producing new dispatch results and market clearing prices. These prices are then adjusted according to the price cap mechanism. Based on the updated market outcomes, NPVs are recalculated, and capacities are updated once more. This iterative loop continues until convergence is achieved.

It is worth noting that the fixed step approach implemented here is aligned with the EVA process tested in ERAA 2024, which uses a “representative unit” approach. Alternative methodologies—such as gradient-descent-based approaches, where the step size can be adapted with each EVA iteration—could be explored to enhance the capacity update mechanism and potentially reduce the number of iterations required to reach EVA equilibrium.

As described in equation (12.3) above, an optional linear decay of the step size is available to reduce the increment gradually over iterations, which can help improve convergence stability. The minimum step size and the number of decay iterations are both configurable; see Section General methodology for the full formulation.

Convergence

Convergence of the capacity update process is determined by evaluating whether the absolute value of all assets’ NPV fall below an indifference threshold. This reflects the assumption that an investor does not proceed with an investment or disinvestment if the NPV is too close to the equilibrium level.

For example, if the threshold is set to 10 k€/MW, the EVA process is considered to have converged once all NPVs lie within the range of –10 k€/MW to +10 k€/MW across all target years. At this point, no further investment or decommissioning is triggered, and the system is deemed to have reached equilibrium.

Using a threshold per MW, rather than the total absolute NPV, avoids bias towards technologies with large or small initial capacities and ensures a consistent, system-wide convergence check across all technologies and stochastic scenarios.

Additional convergence criteria can also be introduced to help identify when market equilibrium has been achieved. For example, capacity changes between consecutive iterations can be

monitored, and if they begin oscillating without progressing towards convergence, the process can be terminated early.

Optimising the convergence of the EVA process is essential for reducing computational complexity. Several strategies can be explored, including:

- Adjusting the capacity update step dynamically (e.g., increasing or decreasing it based on iteration progress).
- Applying differentiated step sizes based on bidding zones or regions. For example, smaller zones such as Malta or Luxembourg can use a smaller step size, whereas larger ones like Germany can use a larger one.
- Implementing a limit to the number of candidates that can be updated per iteration (e.g., updating only the 5 most/least profitable ones).

3.5. Post-processing

3.5.1. Flexibility indicators

3.5.1.1. Background

Assessing system flexibility is crucial for ensuring the reliable integration of variable renewable energy while maintaining security of supply. The EU-Flex model incorporates a dedicated framework to quantify system flexibility, identify potential shortages, and evaluate the ability of different resources to respond to real-time demand fluctuations, forecast errors, and ramping constraints.

Flexibility assessment spans multiple weather years, ensuring that system reliability is evaluated under diverse renewable availability conditions. Key flexibility indicators focus on the ability to handle net residual demand variability, curtailment risks, and additional ramping needs beyond available system capacity.

3.5.1.2. Target

The flexibility assessment aims to:

- Quantify flexibility requirements based on the residual load curve across different timeframes (daily, weekly and seasonal).
- Measure curtailment of variable renewable generation due to system inflexibility, expressed in MWh/year per bidding zone.

- Evaluate the contributions of generation, demand-side response, storage, and cross-border trading towards meeting flexibility needs.
- Determine flexibility needs, assessing the additional system flexibility required to achieve renewable integration and security of supply targets.
- Analyse the system's capability to manage unexpected changes (e.g., forecasting errors) between market timeframes, particularly between DA-UCED and ID-ED.

3.5.1.3. Implementation strategy

The EU-Flex model integrates a dedicated computation module to assess system flexibility and calculate metrics across various market timeframes, utilising both ex-ante and ex-post indicators. Ex-ante metrics provide descriptive insights into system needs, including residual load-based flexibility requirements (daily, weekly and seasonal), maximum ramping requirements, ramping shortfall needs, and forecast error contributions. These indicators offer a forward-looking perspective on the system's flexibility demand.

In contrast, ex-post metrics highlight flexibility gaps, indicating where the system falls short, such as the contributions of different technologies and cross-border interconnections to flexibility, curtailment of variable renewable energy, and curtailment reduction via dummy storage. These metrics are derived from dispatch decisions made by the market models (DA-UCED and ID-ED).

These metrics are derived from the final iteration of the capacity expansion (EVA) process, encompassing results and/or parameters of a given target year (*ty*) and all scenarios ($sy \in SY$). Consequently, while these metrics are inherently indexed by *ty* and *sy*, the indexes are omitted in the equations below for clarity of notation.

Residual load-based flexibility needs

Residual load represents the portion of electricity demand that must be met by dispatchable technologies, including thermal generation, hydro, storage, demand response, and interconnectors[33]. It serves as a key indicator of system flexibility needs and is calculated as the difference between total demand and variable renewable generation:

$$RL_{n,t} = \sum_{s \in S^{\text{load}}} d_{n,s,t} - \sum_{s \in S^{\text{VRE}} \cup S^{\text{must-run}}} g^{\text{tot}}_{n,s,t} \quad \forall n \in N, \forall t \in ty \tag{13.1}$$

which calculates the residual load time series for every bidding zone ($RL_{n,t}$) based on the difference between the total system demand ($d_{n,s,t}$) and the potential generation from VRE (S^{VRE}) and must-run ($S^{\text{must-run}}$) sources. Note that $g^{\text{tot}}_{n,s,t} = \overline{g}_{n,s} g^{\max}_{n,s,t} \forall s \in S^{\text{VRE}}$ and $g^{\text{tot}}_{n,s,t} = \overline{g}_{n,s} g^{\min}_{n,s,t} \forall s \in S^{\text{must-run}}$.

A system with a high share of VRE sources, such as wind and solar, experiences variability across multiple time horizons, from hourly intraday fluctuations to seasonal shifts. To evaluate the

flexibility requirements of the system, it is essential to analyse residual load dynamics at distinct timescales: daily, weekly, and seasonal. This metric is calculated for the ID-ED only.

Daily flexibility need

Daily fluctuations in residual load are primarily driven by demand cycles and solar generation patterns. If residual load were constant throughout the day, dispatchable generation would require no intra-day flexibility. However, rapid load changes or steep ramps in solar output require flexible generation assets.

Figure 12 illustrates the calculation of daily flexibility needs based on hourly residual load. In the figure, the solid purple line represents the hourly residual load, with an average daily residual load of zero. The daily flexibility need is determined as the sum of the highlighted areas.

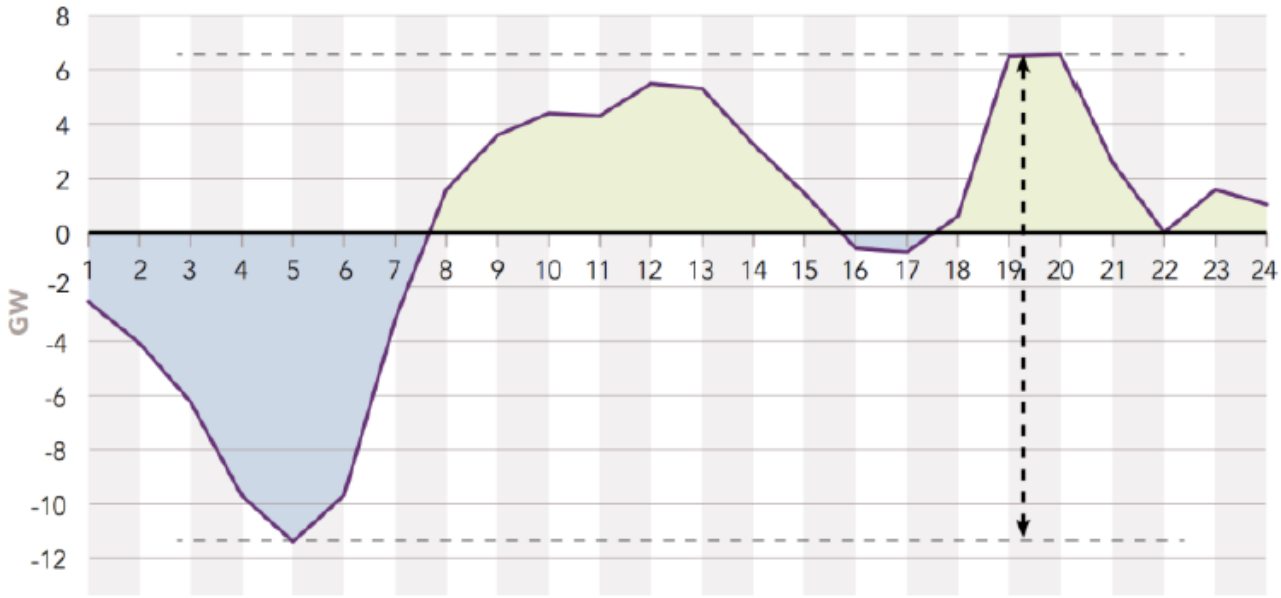


Figure 12: Illustration of daily flexibility needs calculation process. Source: RTE (2015), Bilan prévisionnel de l'équilibre offre-demande.

Mathematically, this calculation begins by determining the daily average residual load:

$$\overline{rl}_{n,d} = \frac{1}{24} \sum_{t \in D_d} RL_{n,t} \quad \forall n \in N, \forall d \in ty \tag{13.2}$$

where:

- d is the index for days.
- $\overline{rl}_{n,d}$ represents the daily average residual load at bidding zone n for day d.

The daily flexibility need is then given by:

$$RL_{\text{daily},n,d} = \sum_{t \in D_d} \left| RL_{n,t} - \overline{rl}_{n,d} \right| \quad \forall n \in N, \forall d \in ty \tag{13.3}$$

A higher deviation indicates a greater need for intra-day flexibility, which can be provided by batteries, gas peakers, or fast-ramping hydro. Summing $RL_{\text{daily},n,d}$ over all days of the year provides the total daily flexibility need for the target year.

Weekly flexibility need

Weekly variations in residual load arise due to weekday vs. weekend demand differences and changes in wind generation patterns. A stable weekly residual load indicates consistent system balancing, while significant fluctuations suggest the need for storage or demand-side response.

Figure 13 illustrates the calculation of weekly flexibility needs based on daily average residual load. In the figure, the solid purple line represents the daily average residual load, with an average weekly residual load of zero. The weekly flexibility need is determined as the sum of the highlighted areas.

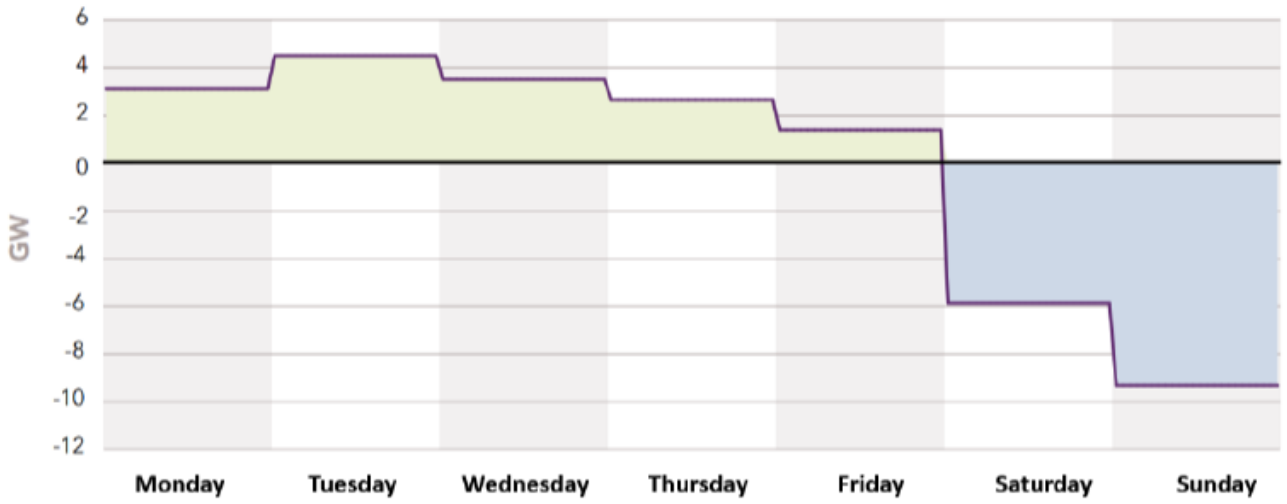


Figure 13: Illustration of weekly flexibility needs calculation process. Source: RTE (2015), Bilan prévisionnel de l'équilibre offre-demande.

Mathematically, this calculation begins by determining the weekly average residual load:

$$\overline{rl}_{n,w} = \frac{1}{7} \sum_{d \in W_w} \overline{rl}_{n,d} \quad \forall n \in N, \forall w \in ty \tag{13.4}$$

where:

- w is the index for weeks.
- $\overline{rl}_{n,w}$ represents the weekly average residual load at bidding zone n for week w.

The weekly flexibility need is then given by summing over all hours in the week, where each hour inherits its day's deviation from the weekly mean:

$$RL_{\text{weekly},n,w} = \sum_{t \in W_w} \left| \overline{rl}_{n,d(t)} - \overline{rl}_{n,w} \right| \quad \forall n \in N, \forall w \in ty \tag{13.5}$$

where $d(t)$ denotes the day containing hour t. Note that $\overline{rl}_{n,d(t)}$ takes the same value for all hours within the same day, meaning each daily deviation is effectively counted 24 times (once per hour). This converts power deviations (MW) into energy units (MWh), quantifying the total energy that must be shifted or stored to balance weekly variations.

A higher weekly deviation suggests that the system requires medium-term storage (e.g., large pumped-hydro and hydro reservoir), semi-base plants (e.g., CCGT, coal, and nuclear power plants), and/or cross-zonal trading capacity. Summing $RL_{\text{weekly},n,w}$ over all weeks of the year provides the total weekly flexibility need for the target year.

Seasonal flexibility need

Seasonal variations in residual load are driven by temperature-sensitive demand (heating in winter, cooling in summer) and seasonal wind/solar generation shifts. Large seasonal variations indicate a need for long-term flexibility solutions, such as hydro reservoirs, hydrogen storage, or interconnectors.

To assess these variations, we first compute the annual average residual load:

$$\overline{rl}_{n,\text{ty}} = \frac{1}{365} \sum_{d=1}^{365} \overline{rl}_{n,d} \quad \forall n \in N \tag{13.6}$$

where:

- *ty* is the index for the year.
- $\overline{rl}_{n,\text{ty}}$ represents the annual average residual load at bidding zone *n* for year *ty*.

The seasonal flexibility need is then given by summing over all hours in the year, where each hour inherits its month's deviation from the annual mean:

$$RL_{\text{seasonal},n,\text{ty}} = \sum_{t \in \text{ty}} \left| \overline{rl}_{n,\text{mo}(t)} - \overline{rl}_{n,\text{ty}} \right| \quad \forall n \in N \tag{13.7}$$

where $mo(t)$ denotes the month containing hour t. Note that $\overline{rl}_{n,\text{mo}(t)}$ takes the same value for all hours within the same month, meaning each monthly deviation is effectively counted once per hour in that month (roughly 720 times for a 30-day month). This converts power deviations (MW) into energy units (MWh), quantifying the total energy that must be shifted or stored to balance seasonal variations.

A high seasonal deviation indicates that the system needs strategic long-term flexibility planning.

Technology and cross-border contributions to flexibility needs

Interconnections between bidding zones provide valuable flexibility by allowing electricity to flow from surplus regions to those with shortages. The contribution of interconnectors, storage, and demand-side resources to flexibility needs (either daily, weekly, or seasonal) is quantified using

dispatch variations rather than absolute dispatch values. This approach measures how much an asset's output varies relative to its mean at each timescale, ensuring that only the variable component of dispatch contributes to flexibility.

Technology contributions:

$$CB_{\text{daily},n,s} = \sum_{d\in \text{ty}} \sum_{t\in D_d} \left(g_{n,s,t} - \overline{g}_{n,s,d}\right) \cdot \text{sign}\left(RL_{n,t} - \overline{rl}_{n,d}\right) \quad \forall n, \forall s \tag{13.8}$$

$$CB_{\text{weekly},n,s} = \sum_{t\in \text{ty}} \left(\overline{g}_{n,s,d(t)} - \overline{g}_{n,s,w(t)}\right) \cdot \text{sign}\left(\overline{rl}_{n,d(t)} - \overline{rl}_{n,w(t)}\right) \quad \forall n, \forall s \tag{13.9}$$

$$CB_{\text{seasonal},n,s} = \sum_{t\in \text{ty}} \left(\overline{g}_{n,s,\text{mo}(t)} - \overline{g}_{n,s,\text{ty}}\right) \cdot \text{sign}\left(\overline{rl}_{n,\text{mo}(t)} - \overline{rl}_{n,\text{ty}}\right) \quad \forall n, \forall s \tag{13.10}$$

Cross-border contributions:

$$CB_{\text{daily},n,l} = \sum_{d\in \text{ty}} \sum_{t\in D_d} -\left(f_{l,t} - \overline{f}_{l,d}\right) \cdot K_{n,l} \cdot \text{sign}\left(RL_{n,t} - \overline{rl}_{n,d}\right) \quad \forall l, \forall n \tag{13.11}$$

$$CB_{\text{weekly},n,l} = \sum_{t\in \text{ty}} -\left(\overline{f}_{l,d(t)} - \overline{f}_{l,w(t)}\right) \cdot K_{n,l} \cdot \text{sign}\left(\overline{rl}_{n,d(t)} - \overline{rl}_{n,w(t)}\right) \quad \forall l, \forall n \tag{13.12}$$

$$CB_{\text{seasonal},n,l} = \sum_{t\in \text{ty}} -\left(\overline{f}_{l,\text{mo}(t)} - \overline{f}_{l,\text{ty}}\right) \cdot K_{n,l} \cdot \text{sign}\left(\overline{rl}_{n,\text{mo}(t)} - \overline{rl}_{n,\text{ty}}\right) \quad \forall l, \forall n \tag{13.13}$$

where $d(t)$ denotes the day containing hour t, $w(t)$ denotes the week containing hour t, and $mo(t)$ denotes the month containing hour t.

In equations (13.8)-(13.10) the daily, weekly, and seasonal contributions of asset *s* to the flexibility needs of bidding zone *n* are computed using **dispatch variations**. The dispatch variation at each timescale represents how much an asset's output deviates from its mean at that timescale. To simplify these equations, $g_{n,s,t}$ is considered as the dispatch of the asset in the intraday market if *s* is a generator or an explicit DSR component, or as the net dispatch (i.e., $g_{n,s,t} = h_{n,s,t} - m_{n,s,t}$) of the asset in the intraday markets if *s* is a storage unit or an implicit DSR component. The terms $\overline{g}_{n,s,d}$, $\overline{g}_{n,s,w}$, $\overline{g}_{n,s,\text{mo}}$, and $\overline{g}_{n,s,\text{ty}}$ are the daily, weekly, monthly, and annual averages of dispatch, respectively.

Similarly, equations (13.11)-(13.13) calculate the daily, weekly, and seasonal contributions of interconnector *l* to the flexibility needs of bidding zone *n* using **flow variations**. The terms $\overline{f}_{l,d}$, $\overline{f}_{l,w}$, $\overline{f}_{l,\text{mo}}$, and $\overline{f}_{l,\text{ty}}$ are the daily, weekly, monthly, and annual averages of power flows over the link *l*. Note that the values are multiplied by the incidence matrix $K_{n,l}$ to represent if the link *l* has a positive (import), negative (export), or null impact on the bidding zone *n*. To be consistent with the sign convention of $g_{n,s,t}$, the flow values are multiplied by -1 in equations (13.11)-(13.13).

The weekly and seasonal contributions are summed over all hours in the year to ensure proper energy units (MWh), consistent with the flexibility need calculations. Each hour inherits its day's, week's, or month's variation and deviation sign.

The sign function in the equations ensures that contributions are properly accounted for:

- If the flexibility need is positive (e.g., residual load is above the average), the asset's dispatch variation must be positive (i.e., dispatch above its mean) for a positive contribution. For instance, if $RL_{n,t} - \overline{rl}_{n,d} > 0$, then the dispatch variation must be positive ($g_{n,s,t} - \overline{g}_{n,s,d} > 0$) so the asset has a positive contribution to the flexibility need.
- If the flexibility need is negative (e.g., residual load is below the average), the asset's dispatch variation must be negative (i.e., dispatch below its mean) for a positive contribution. For instance, if $RL_{n,t} - \overline{rl}_{n,d} < 0$, then the dispatch variation must be negative ($g_{n,s,t} - \overline{g}_{n,s,d} < 0$) so the asset has a positive contribution.

These contributions can be aggregated by technology type (e.g., gas turbines, batteries, demand response) and interconnectors to identify which resource types are most effective at providing flexibility at different timescales. This means that the contributions can be summed over all assets *s* of a given technology type *S* or over all interconnectors *L* to provide a technology-specific or interconnector-specific contribution to flexibility needs.

Ramping needs

Maximum ramping requirement

A key flexibility indicator is the maximum ramping requirement, which quantifies the steepest change in residual load between consecutive time steps[34]:

$$RM_n^{\max} = \max_{t \in \text{ty}} |RL_{n,t} - RL_{n,t-1}| \quad \forall n \in N \tag{13.14}$$

This evaluates if the system is capable of handling load variations, considering operational constraints.

Ramping shortfall

The ramping shortfall indicator quantifies the flexibility lost due to ramping constraints by comparing system dispatch with and without ramping limitations. It is reported as two components, each a **signed** difference:

$$RS_{n,t}^{\text{up}} = C_{n,t}^{\text{ramp}} - C_{n,t}^{\text{no-ramp}} \quad \forall n \in N, \forall t \tag{13.15a}$$

$$RS_{n,t}^{\text{down}} = ENS_{n,t}^{\text{ramp}} - ENS_{n,t}^{\text{no-ramp}} \quad \forall n \in N, \forall t \tag{13.15b}$$

where:

- $RS_{n,t}^{\text{up}}$ is the upward ramping shortfall component in bidding zone *n* at time *t*, derived from curtailment

- $RS^{\text{down}}_{n,t}$ is the downward ramping shortfall component in bidding zone *n* at time *t*, derived from energy not served
- $C^{\text{ramp}}_{n,t}$ is curtailment with ramping constraints (regular intraday dispatch)
- $C^{\text{no-ramp}}_{n,t}$ is curtailment without ramping constraints
- $ENS^{\text{ramp}}_{n,t}$ is energy not served with ramping constraints
- $ENS^{\text{no-ramp}}_{n,t}$ is energy not served without ramping constraints

The aggregated indicators are the signed sums of (13.15a) and (13.15b) over all hours of the assessed year, per bidding zone.

Implementation methodology:

1. Run intraday dispatch with ramping constraints and DA unit commitment decisions (regular ID run)
2. Run intraday dispatch without ramping constraints but keeping DA unit commitment decisions. Only the generator ramping limits are relaxed — $-R^{\text{down}}_i \leq p_{i,t} - p_{i,t-1} \leq R^{\text{up}}_i$, including the start-up and shut-down ramp terms that share those constraint rows. Minimum up/down times, the DA commitment decisions, reserve procurement, maintenance and forced outages are unchanged.
3. Calculate each component as the signed difference in curtailment and in ENS respectively

Positive values indicate that ramping constraints are limiting system flexibility, requiring additional curtailment or load shedding that could be avoided if ramping capabilities were unconstrained.

Contribution to ramping needs

This metric quantifies each technology's contribution to meeting ramping needs during the most extreme ramping events. Technologies contributing positively are those whose dispatch changes align with the sign of residual load changes, indicating they are actively responding to ramping requirements.

$$RC_{n,s} = \frac{\sum_{t \in T^{\text{ramp}}_N} (g_{n,s,t} - g_{n,s,t-1}) \cdot \text{sign}\,(RL_{n,t} - RL_{n,t-1})}{\sum_{t \in T^{\text{ramp}}_N} |RL_{n,t} - RL_{n,t-1}|} \quad \forall n \in N, \forall s \tag{13.16}$$

where:

- $RC_{n,s}$ is the contribution fraction of technology *s* to ramping needs in bidding zone *n*
- T^{ramp}_N is the set of N time steps with the largest absolute changes in residual load $|RL_{n,t} - RL_{n,t-1}|$; N is a configurable parameter ("N worst ramping events"), and by default the metric is computed for N = 1, 10 and 25

- $g_{n,s,t}$ is the dispatch of generator/storage unit s at time t
- $RL_{n,t}$ is the residual load at time t

The numerator captures only dispatch changes that align with (same sign as) the residual load change, while the denominator normalises by the total ramping requirement. This produces fractional contributions that sum to unity across all contributing technologies, showing the relative role of batteries, hydro, and other flexible resources in meeting ramping needs.

Short-term needs

System flexibility is also assessed based on its ability to respond to forecast errors in renewable generation and electricity demand, as well as to respond to unplanned outages. Errors in forecasting can create unexpected imbalances, requiring additional system flexibility to compensate for deviations from expected supply and consumption patterns.

$$FE_{n,t} = RL_{n,t}^{\text{actual}} - RL_{n,t}^{\text{forecasted}} \quad \forall n \in N, \forall t \in \text{ty} \tag{13.17}$$

where $RL_{n,t}^{\text{actual}}$ is the residual load used in the ID-ED market, and $RL_{n,t}^{\text{forecasted}}$ is the forecasted residual load used in the DA-UCED market.

- When the actual residual load is higher than the forecasted ($RL_{n,t}^{\text{actual}} > RL_{n,t}^{\text{forecasted}}$, thus $FE_{n,t} > 0$), either renewable generation was over-forecasted and/or demand was under-forecasted. As such, the system needs to compensate with an upward adjustment: using upward reserves, increasing generation, decreasing demand of DSR resources, storage discharging, imports, or other flexible resources.
- When the actual residual load is lower than the forecasted ($RL_{n,t}^{\text{actual}} < RL_{n,t}^{\text{forecasted}}$, thus $FE_{n,t} < 0$), either renewable generation was under-forecasted and/or demand was over-forecasted. As such, the system needs to compensate with a downward adjustment: using downward reserves, decreasing generation, increasing demand of DSR resources, storage charging, exports, or other flexible resources.

Total forecast error energy

The total forecast error energy sums the hourly forecast errors (13.17) over the target year. Upward and downward errors are summed separately, so that they do not cancel each other out:

$$FE_n^{\text{tot,up}} = \sum_{t \in \text{ty}} \max\left(FE_{n,t}, 0\right) \quad \forall n \in N \tag{13.18a}$$

$$FE_n^{\text{tot,down}} = \sum_{t \in \text{ty}} \min\left(FE_{n,t}, 0\right) \quad \forall n \in N \tag{13.18b}$$

$FE_n^{\text{tot,up}}$ is the energy of upward adjustments that the system must provide in ID-ED, and $FE_n^{\text{tot,down}}$ (a negative value) that of downward adjustments.

Percentile forecast error

Following the FNA methodology (Article 10), the short-term flexibility needs are determined as percentiles of the probability distribution of the residual load forecast errors. The percentiles are taken on the signed series $FE_{n,t}$, without separating upward and downward errors beforehand. The upper tail ($q \in \{99.9, 99\}$) represents the upward need and the lower tail ($q \in \{0.1, 1\}$) the downward need. The 99 and 1 percentiles are computed as sensitivities. The percentiles are fixed and not configurable.

For each climate year, the percentiles are computed over the hours of the target year:

$$FE_n^q = \text{percentile}_q \left(FE_{n,t} \mid t \in ty \right) \quad \forall n \in N, \forall q \in \{99.9, 99\} \tag{13.19a}$$

$$FE_n^q = \text{percentile}_q \left(FE_{n,t} \mid t \in ty \right) \quad \forall n \in N, \forall q \in \{0.1, 1\} \tag{13.19b}$$

In addition, the percentiles are computed on the forecast errors pooled across all climate years of the run. This is not equivalent to averaging the percentiles of the individual climate years:

$$FE_n^{q,\text{pool}} = \text{percentile}_q \left(FE_{n,t,\text{cy}} \mid t \in ty, cy \in CY \right) \quad \forall n \in N, \forall q \in \{99.9, 99, 1, 0.1\} \tag{13.19c}$$

Because the percentiles are taken on the signed series, an upper tail percentile can be negative (and a lower tail percentile positive) when the forecast errors of a bidding zone are predominantly of one sign.

Short-term shortfall

The short-term shortfall indicators quantify instances where the system's available flexibility is insufficient to compensate for forecast errors. Two complementary approaches are implemented:

Simulation-based short-term shortfall

The simulation-based approach directly compares outcomes between day-ahead forecasted and intraday actual market clearing to identify shortfall events.

A short-term shortfall indicator measures instances where the system's available flexibility is insufficient to compensate for forecast errors:

$$FE_{n,t}^{\text{curt}} = ct_{n,t}^{\text{base,actual}} - ct_{n,t}^{\text{base,forecasted}} \quad \forall n \in N, \forall t \in ty \tag{13.20}$$

where $ct_{n,t}^{\text{base,actual}}$ is the curtailment calculated based on actual renewable generation in the ID-ED market, and $ct_{n,t}^{\text{base,forecasted}}$ is the curtailment calculated based on forecasted renewable generation in the DA-UCED market.

We can then calculate the total short-term curtailment shortfall over the entire year as:

$$FE_n^{\text{curt, tot}} = \sum_{t \in \text{ty}} FE_{n,t}^{\text{curt}} \quad \forall n \in N \tag{13.21}$$

and the maximum short-term curtailment shortfall as:

$$FE_{n}^{\text{curt, max}} = \max_{t \in \text{ty}} FE_{n,t}^{\text{curt}} \quad \forall n \in N \tag{13.22}$$

Similarly, we can define the short-term energy not served (ENS) shortfall as:

$$FE_{n,t}^{\text{ens}} = g_{n,s,t}^{\text{actual}} - g_{n,s,t}^{\text{forecasted}} \quad \forall n \in N, \forall t \in ty, s \in S_{n}^{\text{LoL}} \tag{13.23}$$

where $g_{n,s,t}^{\text{actual}}$ is the load shedding calculated in the ID-ED market, and $g_{n,s,t}^{\text{forecasted}}$ is the load shedding calculated in the DA-UCED market.

We can then calculate the total short-term ENS shortfall over the entire year as:

$$FE_{n}^{\text{ens, tot}} = \sum_{t \in \text{ty}} FE_{n,t}^{\text{ens}} \quad \forall n \in N \tag{13.24}$$

and the maximum short-term ENS shortfall as:

$$FE_{n}^{\text{ens, max}} = \max_{t \in \text{ty}} FE_{n,t}^{\text{ens}} \quad \forall n \in N \tag{13.25}$$

Probabilistic short-term shortfall

The probabilistic approach quantifies short-term flexibility requirements based on the statistical distribution of forecast errors and residual flexibility capacity available in the day-ahead schedule.

Forecast error distribution: For each system condition c (defined by season and time-of-day), forecast errors are aggregated across climate years to build an empirical distribution:

$$FE_{c,n}^{p_{\text{high}}} = \text{percentile}_{p_{\text{high}}} \left(FE_{n,t} \mid t \in c \right) \quad \forall c, \forall n \tag{13.26}$$

$$FE_{c,n}^{p_{\text{low}}} = \text{percentile}_{p_{\text{low}}} \left(FE_{n,t} \mid t \in c \right) \quad \forall c, \forall n \tag{13.27}$$

where p_{high} (e.g., 99.9) captures extreme upward errors and p_{low} (e.g., 0.1) captures extreme downward errors.

Residual flexibility capacity: The available flexibility in the day-ahead dispatch after accounting for ramping limits and reserves:

$$F_{n,t}^{\text{up}} = \sum_{s \in S^{\text{disp}}} \left[\min \left(p_{n,s}^{\max} \cdot \overline{g}_{n,s},\ g_{n,s,t}^{\text{DA}} + r_{n,s}^{\text{ramp,up}} \right) - g_{n,s,t}^{\text{DA}} \right] - R_{n,t}^{\text{FCR,up}} - R_{n,t}^{\text{FRR,up}} \quad \forall n, \forall t \tag{13.28}$$

$$F_{n,t}^{\text{down}} = \sum_{s \in S^{\text{disp}}} \left[g_{n,s,t}^{\text{DA}} - \max \left(p_{n,s}^{\min} \cdot \overline{g}_{n,s},\ g_{n,s,t}^{\text{DA}} - r_{n,s}^{\text{ramp,down}} \right) \right] - R_{n,t}^{\text{FCR,down}} - R_{n,t}^{\text{FRR,down}} \quad \forall n, \forall t \tag{13.29}$$

where S^{disp} excludes renewable and shedding generators as well as all storage units (hydro reservoirs, pumped hydro, batteries and implicit DSR), $r_{n,s}^{\text{ramp}}$ are hourly ramp limits, and $R_{n,t}^{\text{FCR,up}}$, $R_{n,t}^{\text{FCR,down}}$, $R_{n,t}^{\text{FRR,up}}$, and $R_{n,t}^{\text{FRR,down}}$ are the committed reserves for FCR and FRR in the upward and downward directions, respectively.

Uncovered flexibility needs: For each hour, the forecast error percentile for its condition is compared with available flexibility:

$$U^{\text{up}}_{n,t} = \max\left(0,\ FE^{p_{\text{high}}}_{c(t),n} - F^{\text{up}}_{n,t}\right) \quad \forall n, \forall t \tag{13.30}$$

$$U^{\text{down}}_{n,t} = \max\left(0,\ \left|FE^{p_{\text{low}}}_{c(t),n}\right| - F^{\text{down}}_{n,t}\right) \quad \forall n, \forall t \tag{13.31}$$

where $c(t)$ maps each hour to its system condition.

Expected shortfalls: The probabilistic expected curtailment and energy not served:

$$E^{\text{ENS}}_{n,t} = U^{\text{up}}_{n,t} \cdot \frac{100 - p_{\text{high}}}{100} \quad \forall n, \forall t \tag{13.32}$$

$$E^{\text{curt}}_{n,t} = U^{\text{down}}_{n,t} \cdot \frac{p_{\text{low}}}{100} \quad \forall n, \forall t \tag{13.33}$$

These metrics quantify the expected magnitude of flexibility shortfalls weighted by their probability of occurrence. Note that $U^{\text{up}}_{n,t}$ (uncovered upward need, from high positive forecast errors) leads to energy not served, while $U^{\text{down}}_{n,t}$ (uncovered downward need, from low negative forecast errors) leads to curtailment.

Contributions to short-term needs

The contributions of different technologies and interconnectors to managing forecast errors are quantified using the **DA-to-ID dispatch adjustment**, i.e. how much each asset changed its output from its day-ahead schedule in response to the forecast error:

$$FE^{\text{cont}}_{n,s} = \sum_{t \in \text{ty}} \left(g^{\text{actual}}_{n,s,t} - g^{\text{forecasted}}_{n,s,t}\right) \cdot \text{sign}\left(FE_{n,t}\right) \quad \forall n, \forall s \tag{13.34}$$

$$FE^{\text{cont}}_{n,l} = \sum_{t \in \text{ty}} \left(f^{\text{actual}}_{l,t} - f^{\text{forecasted}}_{l,t}\right) \cdot K_{n,l} \cdot \text{sign}\left(FE_{n,t}\right) \quad \forall l, \forall n \tag{13.35}$$

where $g^{\text{actual}}_{n,s,t}$ and $g^{\text{forecasted}}_{n,s,t}$ are the intraday and day-ahead dispatch of asset *s* in bidding zone *n* at time *t*, and $f^{\text{actual}}_{l,t}$ and $f^{\text{forecasted}}_{l,t}$ are the intraday and day-ahead flows over interconnector *l*. A positive contribution indicates that the asset adjusted its output in the same direction as the forecast error (i.e. it helped cover the short-term need), while a negative contribution indicates it moved against the forecast error.

Curtailment of variable renewable energy

Curtailment occurs when system flexibility is insufficient to absorb excess variable renewable energy (VRE) generation, leading to a reduction in available renewable output. This can result from transmission congestion, reserve shortages, ramping constraints, or maintenance outages.

The baseline curtailment is computed as:

$$ct^{\text{base}}_{n,t} = \sum_{s \in S^{\text{VRE}}} \max\left(0, g^{\max}_{n,s,t} - g_{n,s,t}\right) \quad \forall n \in N, \forall t \in ty \tag{13.36}$$

$$CT^{\text{base}}_{n} = \sum_{t} ct^{\text{base}}_{n,t} \quad \forall n \in N \tag{13.37}$$

where:

- $ct_{n,t}^{\text{base}}$ represents the baseline curtailment at bidding zone *n* and time *t*.
- CT_{n}^{base} represents the total baseline curtailment at bidding zone *n* over all time steps.
- $g_{n,s,t}^{\max}$ represents the maximum available generation from source *s* at bidding zone *n* and time *t*.

Curtailment may increase when grid constraints prevent full utilisation of renewable energy, requiring additional flexibility sources such as storage, interconnections, or demand-side response

Curtailment reduction through dummy storage

To assess the potential of storage to mitigate curtailment, the EU-Flex model implements a **dummy storage optimisation formulation** integrated within PyPSA. This approach goes beyond simple absorption terms to model realistic storage constraints and dispatch behaviour, taking Economic Dispatch (ED) results as input parameters and re-optimising with additional dummy storage flexibility.

Dummy storage units represent **idealised flexibility resources** with perfect efficiency, providing a metric for curtailment reduction potential rather than realistic investment pathways. The formulation determines either:

- the *minimum dummy storage capacity* needed to achieve curtailment reduction targets, or
- the *economically optimal dummy storage configuration* considering system-wide costs.

The dummy storage problem is solved with the solver options mapped to the selected solver (*configurable*: Dummy storage solver options; by default `highs-lp-baseline` for HiGHS and `gurobi-optimal-dummy-storage` for Gurobi), independent of the solver options used for the market models; only the thread count is taken over, and solvers without a mapping use the solver options of the market models. The default options yield a vertex (basic) solution: simplex for HiGHS, and barrier with crossover for Gurobi. An interior-point solution without crossover can hide excess dummy storage capacity within the relative stopping tolerance, because the objective mixes MW of capacity with a large spillage penalty.

Integration of TSO/DSO network needs

The dummy storage optimisation can also incorporate TSO/DSO network needs by incorporating an exogenously defined curtailment curve from system operators. This curve sets the needed curtailment target for TSO/DSO operations, and the final curtailment to be used in the dummy storage optimisation is the maximum between the market-based curtailment and the TSO/DSO-defined curtailment. This ensures that the dummy storage optimisation respects both market dynamics and operational requirements. **Figure 14** illustrates this concept, where the final curtailment target is determined by the higher of the two curves.

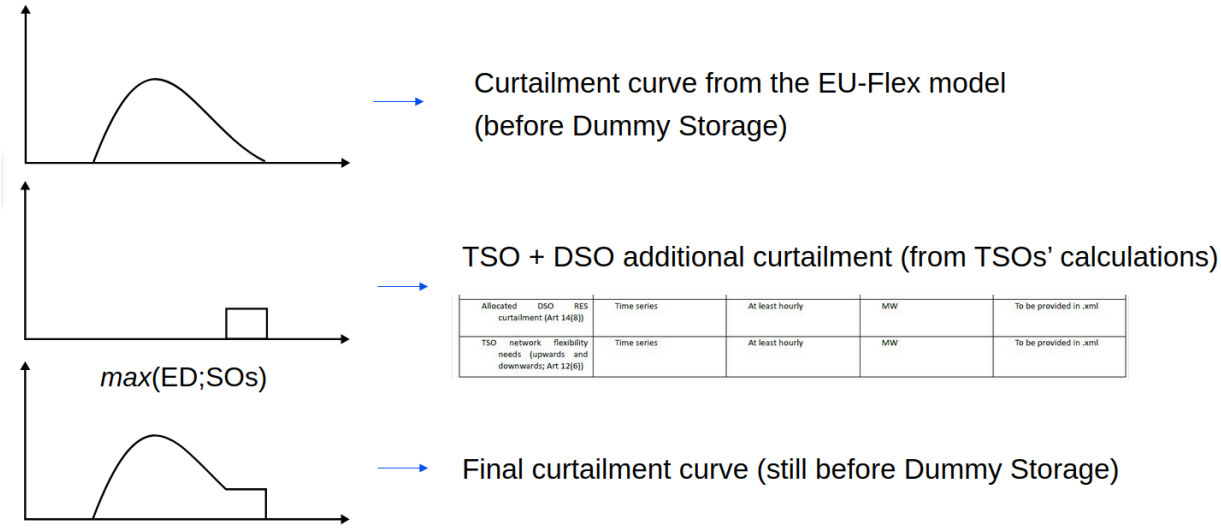


Figure 14: Integrating TSO/DSO network needs in the dummy storage computations.

In order to achieve this with the EU-Flex approach, which directly takes in results from the market model rather than a curtailment curve, this is achieved by:

1. Computing curtailment adjusted necessary based on network needs in each BZ.

$$ct_{n,t}^{\text{adj}} = \max\left(ct_{n,t}^{\text{orig}},\ ct_{n,t}^{\text{net}}\right) \quad \forall n \in N, \forall t \in T \tag{13.38}$$

2. Reducing the renewable power output obtained from the market models by the amount necessary to achieve the targeted curtailment level from network needs.

$$\sum_{s \in S^{\text{VRE}}} g_{n,s,t}^{\text{VRE,adj}} = \sum_{s \in S^{\text{VRE}}} g_{n,s,t}^{\text{VRE,orig}} - \left(ct_{n,t}^{\text{adj}} - ct_{n,t}^{\text{orig}}\right)_+ \tag{13.39}$$

   where $(x)_+ = \max(x, 0)$ denotes the positive part of x.

3. Increasing the conventional generator power output of the same bidding zone by the equivalent reduction in renewable one in order to still meet demand, proportionally to the headroom $H_{n,s,t} = \overline{g}_{n,s}\, a_{n,s,t} - g_{n,s,t}^{\text{conv,orig}}$ of the clustered conventional generators S_n^{conv} of bidding zone n. Load shedding, load spillage and storage are not adjusted. If $\Delta_{n,t} > \sum_{s' \in S_n^{\text{conv}}} H_{n,s',t}$, the headroom cannot compensate the additional curtailment and the dummy storage optimisation fails.

$$\begin{aligned} g_{n,s,t}^{\text{conv,adj}} &= g_{n,s,t}^{\text{conv,orig}} + \Delta_{n,t} \cdot \frac{H_{n,s,t}}{\sum_{s' \in S_n^{\text{conv}}} H_{n,s',t}}, \\ \Delta_{n,t} &= \left(ct_{n,t}^{\text{adj}} - ct_{n,t}^{\text{orig}}\right)_+ \end{aligned} \quad \forall s \in S_n^{\text{conv}}, \forall n \in N, \forall t \in T \tag{13.40}$$

4. Adding the additional curtailment to the allowed curtailment of the curtailment reduction target (13.51), since the network needs curtailment does not count against it: $\sum_{t \in T} \Delta_{n,t}$ is added to the right-hand side of (13.51).

No TSO/DSO network needs data is available yet. The network needs $ct^{\text{net}}_{n,t}$ are therefore random mock data, drawn uniformly between 0 and 80% of the RES availability per hour and bidding zone. They are disabled by default (*configurable*: Dummy storage network needs (TSO/DSO)).

This approach was followed, in agreement with ACER, as it was deemed most representative of the realities of network needs, where renewable production is further curtailed to ensure the network is not overloaded. An example resulting curve with our approach is given by **Figure 15** below

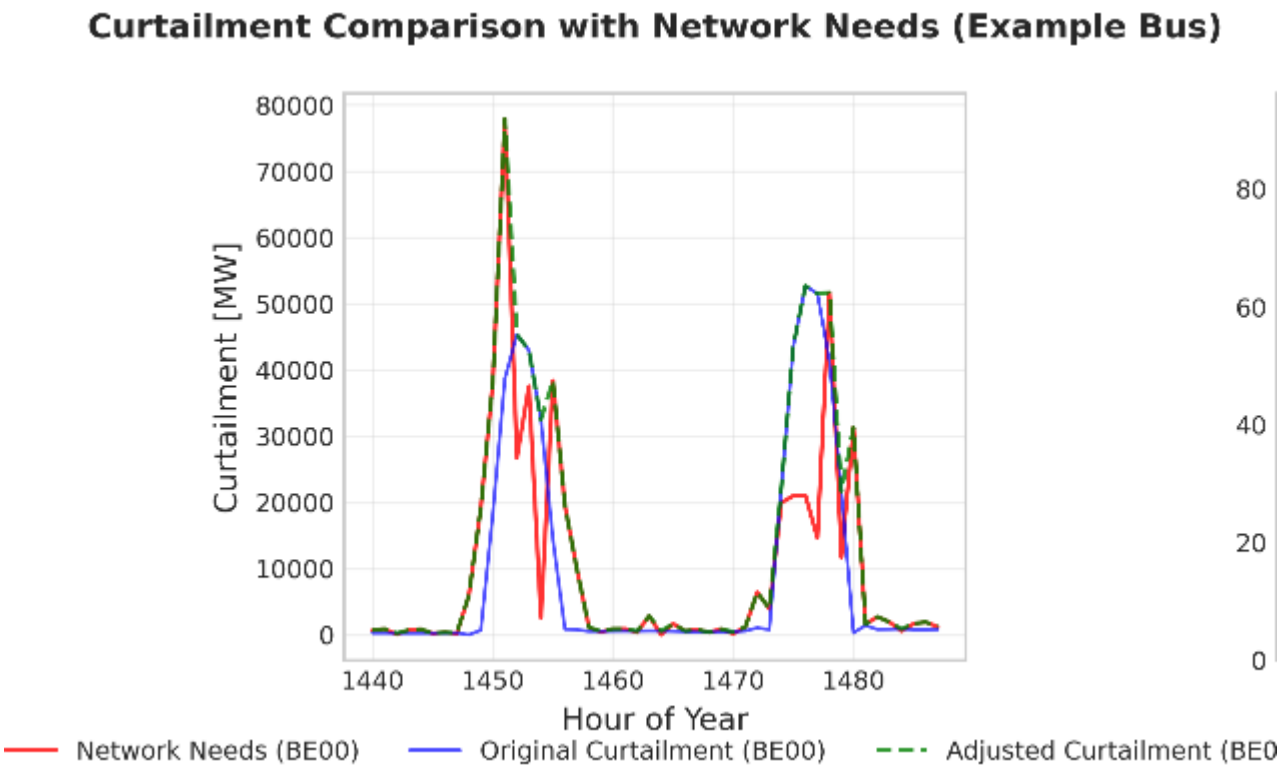


Figure 15: Example implementation of TSO/DSO needs curtailment adjustment in the EU-Flex model.

Objective functions

Two alternative formulations are provided:

System cost minimisation (economic):[48]

$$\min \quad \sum_{t \in T} \left[\sum_{s \in S^{\text{gen}}} c^{\text{marg}}_{n,s,t}\, g_{n,s,t} + \sum_{s \in S^{\text{store}}} c^{\text{marg}}_{n,s,t}\, h_{n,s,t} \right] + \sum_{s \in S^{\text{ds}}} c^{\text{ds}}_{n,s}\, \overline{h}^{\text{ds}}_{n,s} \quad \forall n \in N \tag{13.41}$$

Capacity minimisation (technical upper bound):

$$\min \quad \sum_{s \in S^{\text{ds}}} \sum_{n \in N} \overline{h}^{\text{ds}}_{n,s} - \sum_{t \in T} w_t \sum_{n \in N} \sum_{s \in S^{\text{spill}}} c^{\text{spill}}\, g_{n,s,t} \tag{13.42}$$

where w_t is the snapshot weighting. Since this objective discards PyPSA's default marginal-cost terms entirely, the load spillage penalty c^{spill} (*configurable*: Dummy storage load spillage penalty) is re-added explicitly so that spillage is not preferred for free over installing dummy storage capacity — see "Load spillage and load shedding" below. As $g_{n,s,t} \leq 0$ for $s \in S^{\text{spill}}$, the penalty term is always non-negative. Load shedding is fixed to the ED dispatch and therefore needs no penalty. Under the system cost minimisation objective (13.41), no such term is needed: both slacks are members of S^{gen}, so their marginal costs are already priced through $c^{\text{marg}}_{n,s,t}\, g_{n,s,t}$.

Constraints

Nodal power balance

$$\sum_{s \in S^{\text{gen}}} g_{n,s,t} + \sum_{s \in S^{\text{store}}} (h_{n,s,t} - m_{n,s,t}) - \sum_{s \in S^{\text{load}}} d_{n,s,t} - \sum_{l} K_{n,l} f_{l,t} = 0 \quad \forall t \in T, \forall n \in N \tag{13.43}$$

Generator limits

$$0 \leq g_{n,s,t} \leq \overline{g}_{n,s}\, a_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{gen}} \tag{13.44}$$

where $a_{n,s,t}$ is the availability factor and $\overline{g}_{n,s}$ is the nominal capacity. For the clustered renewable generator per bidding zone, $\overline{g}_{n,s}$ is the summed installed capacity and $a_{n,s,t}$ the capacity-weighted availability, so that $a_{n,s,t}\,\overline{g}_{n,s}$ equals the summed availability of the clustered renewable generators.

Storage dynamics

$$\begin{aligned} soc_{n,s,t} = (1 - \lambda_{n,s})\, soc_{n,s,t-1} + \eta^{\text{ch}}_{n,s} m_{n,s,t} - \tfrac{1}{\eta^{\text{dis}}_{n,s}} h_{n,s,t} \\ + inflow_{n,s,t} - spillage_{n,s,t} \end{aligned} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store}} \tag{13.45}$$

State of charge bounds

$$0 \leq soc_{n,s,t} \leq \overline{e}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store}} \tag{13.46}$$

Dummy storage power capacity limits

For regular storage units:

$$0 \leq m_{n,s,t} \leq \overline{m}_{n,s}, \quad 0 \leq h_{n,s,t} \leq \overline{h}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store}} \setminus S^{\text{ds}} \tag{13.47}$$

For dummy storage units:

$$0 \leq m_{n,s,t} \leq \overline{h}^{\text{ds}}_{n,s}, \quad 0 \leq h_{n,s,t} \leq \overline{h}^{\text{ds}}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{ds}} \tag{13.48}$$

With perfect efficiency and no throughput cost, simultaneous charging and discharging of a dummy storage is free, so the linear program has degenerate solutions with arbitrary cycling. To speed up the simplex solve and tighten the linear relaxation, the convex hull of the cyclic dummy storage without simultaneous operation (Pozo, Model 3) is added, with $soc_{n,s,t-1}$ the state of charge at the start of snapshot t (cyclic, so that $t-1$ of the first snapshot is the last snapshot) and w_t the snapshot duration:

$$m_{n,s,t} + h_{n,s,t} \leq \overline{h}^{\mathrm{ds}}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{ds}} \tag{13.57}$$

$$soc_{n,s,t-1} + w_t\, m_{n,s,t} \leq \rho^{\mathrm{ds}}_{n,s}\, \overline{h}^{\mathrm{ds}}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{ds}} \tag{13.58}$$

$$soc_{n,s,t-1} - w_t\, h_{n,s,t} \geq 0 \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{ds}} \tag{13.59}$$

The hull requires $0 < w_t \leq \rho^{\mathrm{ds}}_{n,s}$. It removes the cycling where the dummy storage capacity binds, but it does not forbid simultaneous operation where the capacity is slack. The remaining degenerate cycling is removed in post-processing by netting the charging and discharging of each dummy storage per snapshot, $h_{n,s,t} \leftarrow \max(h_{n,s,t} - m_{n,s,t}, 0)$ and $m_{n,s,t} \leftarrow \max(m_{n,s,t} - h_{n,s,t}, 0)$, which leaves the state of charge, the net dispatch and the capacity unchanged.

Dummy storage energy-power ratio

$$\overline{e}_{n,s} = \rho^{\mathrm{ds}}_{n,s} \cdot \overline{h}^{\mathrm{ds}}_{n,s} \quad \forall n \in N, \forall s \in S^{\mathrm{ds}} \tag{13.49}$$

Link capacity limits

$$F^{\min}_{l} \leq f_{l,t} \leq F^{\max}_{l} \quad \forall t \in T, \forall l \in L \tag{13.50}$$

Curtailment reduction target

$$\sum_{t \in T} \sum_{s \in S^{\mathrm{VRE}}} \left(a_{n,s,t}\overline{g}_{n,s} - g_{n,s,t}\right) \leq C^{\mathrm{target}}_{n} \sum_{t \in T} \sum_{s \in S^{\mathrm{VRE}}} a_{n,s,t}\overline{g}_{n,s} \quad \forall n \in N \tag{13.51}$$

where the target C^{target}_{n} is the maximum share of the available VRE energy in bidding zone *n* that may still be curtailed (*configurable*: Dummy storage curtailment targets, 5% by default, or per bidding zone with Dummy storage per-bidding-zone curtailment targets).

Renewable dispatch lower bound

$$g_{n,s,t} \geq g^{\mathrm{ED}}_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{VRE}} \tag{13.52}$$

Conventional generation bounds

$$g^{\min,\mathrm{ds}}_{n,s,t}\, \overline{g}_{n,s} \leq g_{n,s,t} \leq g^{\mathrm{ED}}_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\mathrm{gen}} \setminus S^{\mathrm{VRE}} \tag{13.53}$$

$$g^{\min,\mathrm{ds}}_{n,s,t} = \frac{1}{\overline{g}_{n,s}} \sum_{s' \in S^{\mathrm{conv}}_{n}} \min\left(\max\left(\delta^{\mathrm{floor}}_{n,s'}\, \overline{g}_{n,s'}\, g^{\min}_{n,s',t}\, u_{n,s',t},\ g^{\mathrm{must-run}}_{n,s',t}\right),\ g^{\mathrm{ED}}_{n,s',t}\right)$$

All conventional generators of a bidding zone, including must-run generators (e.g. nuclear), are aggregated into one clustered conventional generator in the dummy storage network, which keeps the summed installed capacity as $\overline{g}_{n,s}$ with the capacity-weighted availability as $g^{\max}_{n,s,t}$. The technical minimum of the generators in S^{floor}_{n} and the must-run requirement of all conventional generators S^{conv}_{n} of the bidding zone are therefore aggregated per bidding zone and applied as the conventional floor $g^{\min,\mathrm{ds}}_{n,s,t}$ on the dispatch of the clustered conventional generator, so that renewable and dummy storage dispatch cannot substitute for them under a tight curtailment target. Per generator, the technical minimum is the ED lower bound $\overline{g}_{n,s'}\, g^{\min}_{n,s',t}$ times the ED commitment status $u_{n,s',t}$ for generators that are committable in the ED, and $u_{n,s',t} = 1$ for the

other generators, whose DA commitment is already embedded in $g^{\min}_{n,s',t}$. The must-run requirement $g^{\text{must-run}}_{n,s',t}$ is the availability-derated requirement of equation (2.9), not scaled by the commitment status. The set $S^{\text{floor}}_n \subseteq S^{\text{conv}}_n$ holds the generators of the selected conventional carriers (*configurable*: Dummy storage conventional floor carriers), and $\delta^{\text{floor}}_{n,s'}$ is 1 for generators in S^{floor}_n and 0 otherwise. By default all conventional carriers are selected; an empty selection keeps only the must-run requirement, which always applies, and selected carriers that are not conventional carriers of the ED network raise an error. Unlike the main dispatch models, this simplified network carries no slack variable, so the floor is capped at the ED dispatch $g^{\text{ED}}_{n,s',t}$ of each generator, which keeps it feasible against the upper bound of the cluster; negative $g^{\min}_{n,s',t}$ or must-run requirements raise an error, as does a conventional dispatch $g^{\text{ED}}_{n,s',t}$ below -10^{-6} MW, while smaller negative values from solver tolerances are set to zero. Bidding zones without floored generators have $g^{\min,\text{ds}}_{n,s,t} = 0$. Note that $g^{\min}_{n,s',t}$ of the ED also includes the lower bounds from blocked down-reserves and fixed DA dispatch of DSR, which then enter the floor.

> Note: electrolysers are not considered as conventional generators. As such, their dispatch is added to the demand curve, meaning its is kept fixed.

Fixed operation of non-dummy storage

$$m_{n,s,t} = m^{\text{ED}}_{n,s,t}, \quad h_{n,s,t} = h^{\text{ED}}_{n,s,t} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{store}} \setminus S^{\text{ds}} \tag{13.54}$$

Optional fixed flows

$$f_{l,t} = f^{\text{ED}}_{l,t} \quad \forall t \in T, \forall l \in L \tag{13.55}$$

Load spillage and load shedding (feasibility slack)

To avoid infeasibilities when the curtailment target, the conventional floor (13.53), and the fixed ED-based bounds above cannot be jointly satisfied, two slack generators are available at every bus, bounded as:

$$g^{\min}_{n,s,t}\,\overline{g}_{n,s} \le g_{n,s,t} \le g^{\max}_{n,s,t}\,\overline{g}_{n,s} \quad \forall t \in T, \forall n \in N, \forall s \in S^{\text{LoL}} \cup S^{\text{spill}} \tag{13.56}$$

- **Load shedding** ($s \in S^{\text{LoL}}$): carried over unconditionally from the input ED network, representing unmet demand. It is fixed to the ED dispatch, $g_{n,s,t} = g^{\text{ED}}_{n,s,t}$, so that dummy storage cannot be sized to replace load shedding of the market models.

- **Load spillage** ($s \in S^{\text{spill}}$, *configurable*: Dummy storage enable load spillage): represents surplus generation that cannot be absorbed even with full dummy storage charging. Bounded as $g^{\min}_{n,s,t} = -1$, $g^{\max}_{n,s,t} = 0$ (negative-only dispatch) with a fixed marginal cost of -4500 €/MWh, so it is only dispatched as a last resort.

Expected dispatch behaviour

The dummy storage dispatch behaviour is governed by the constraints above:

- **Charging during curtailment**: Due to constraint (13.52), renewable generation cannot fall below ED levels, so dummy storage charges ($m_{n,s,t} > 0$) when curtailment would otherwise occur.
- **Discharging for load serving**: Dummy storage discharges ($h_{n,s,t} > 0$) during periods of positive residual load, substituting for conventional generation within the bounds established by constraint (13.53), down to the conventional floor $g^{\min,\mathrm{ds}}_{n,s,t}$.
- **Conventional floor**: Constraint (13.53) prevents dummy storage and renewable dispatch from displacing conventional generation below its technical minimum and must-run requirement (e.g. nuclear) at bidding zones where it applies.
- **No simultaneous cycling**: The hull constraints (13.57)-(13.59) remove simultaneous charging and discharging of dummy storage where its capacity binds, and the netting after the solve removes the remaining degenerate overlap.
- **Feasibility slack as a last resort**: Load spillage (13.56) only activates when the curtailment target and conventional floor cannot otherwise be jointly satisfied; under capacity minimisation (13.42) its dispatch is discouraged via the configurable penalty c^{spill}.
- **Economic merit order** (under system cost minimisation): The optimisation displaces expensive conventional generators first, following economic efficiency principles.
- **Technical minimum capacity** (under capacity minimisation): The model determines the absolute minimum dummy storage capacity needed to achieve curtailment reduction targets, independent of economic considerations.
- **Lossless storage**: Dummy storage is modelled as lossless, with $\eta^{\mathrm{ch}}_{n,s} = \eta^{\mathrm{dis}}_{n,s} = 1$ and $\lambda_{n,s} = 0$; the model raises an error for other values. This is a deliberate modelling choice: the dummy storage measures the flexibility needed to reach the curtailment target independently of a specific storage technology, and the convex hull formulation (13.57)–(13.59) assumes lossless storage. Charging and discharging efficiencies and standing losses are therefore not yet part of the methodology; including them is a possible future extension.
- **Zonal vs cross-zonal flexibility**: When constraint (13.55) is enforced (fixed flows), dummy storage operates independently within each bidding zone. When relaxed, dummy storage can provide cross-zonal flexibility services.

This formulation serves as a **flexibility indicator** within the EU-Flex framework, providing quantitative metrics for the curtailment reduction potential achievable through idealised storage deployment.

3.5.2. Model outputs

3.5.2.1. Background

The modelling platform runs hundreds of simulations, generating vast amounts of data. This poses challenges regarding data storage limitations and the extra computational time needed for post-processing. While it's impractical to retain all results, certain key outcomes—such as CO2 emissions by scenario, market prices, and flexibility and adequacy metrics—are essential for the analysis.

Thus, it's crucial to ensure that sufficient results are stored during each iteration, offering insights into both the final and some interim results. These interim results can assist in model optimisation or shed light on the behaviour of specific components. This section describes the results that are processed and stored from the model. It's worth noting that this is not an exhaustive list; during the implementation process, other significant metrics may arise that warrant storage.

3.5.2.2. Target

This section details the process of collecting results, identifying relevant outputs, processing data, and storing key insights from the model.

Relevant outputs must provide meaningful insights into the model's performance and decision-making processes. The model should offer visibility into dispatch decisions, reserve market outcomes, and pricing dynamics across bidding zones, countries, and time steps. Each Monte Carlo simulation generates a vast amount of data and storing all individual results is impractical. Instead, key results can be extracted and aggregated to provide a representative value along with a confidence interval. These insights enhance decision-making by offering a detailed understanding of system operations and market behaviour.

3.5.2.3. Implementation strategy

Table 5 provides a summary of the expected results, including their units, whether they are time-series results, and the workflow stages where these results are generated. For outputs derived from Monte Carlo scenarios, the results are usually presented as aggregated values with confidence intervals. Depending on the level of detail required for the specific result presentation, the time series are summed to reduce the amount of data stored. For outputs spanning multiple iterations, the EVA column in Table 5 specifies whether results are stored for intermediary iterations (✓) or only for the final iteration (empty).

Table 5: Summary of results expected from the model.

Result	Units	Time series	Pre-optimisation	Monte Carlo	Monte Carlo	EVA
				DA-UCED	ID-ED	
Market and Economic Results						
Market prices	€/MWh	✓		✓	✓	
Average prices	€/MWh				✓	
Price volatility	€/MWh				✓	
Zero/negative price hours	hours				✓	
Total generation by technology per day	MWh	✓		✓	✓	
Net power transfer between bidding zones	MWh	✓		✓	✓	
Reserve capacity per generator	MW	✓		✓		
Reservoir storage levels	MWh	✓	✓			
Storage units charging	MW	✓			✓	
Supply	MWh	✓			✓	
Withdrawal	MWh	✓			✓	
Total CO2 emission	tonnes CO2			✓	✓	
Demand timeseries	MW	✓			✓	
Load spillage timeseries	MW	✓			✓	
Capacity Expansion Results (EVA)						
Commissioned capacity	MW					✓
Capacity mothballed	MW					✓

Result	Units	Time series	Pre-optimisation	Monte Carlo	Monte Carlo	EVA
Decommissioned capacity	MW					✓
NPV per MW	EUR/MW					✓
Final production capacities	MW				✓	
Final storage capacities	MWh				✓	
Flexibility Indicators						
Residual Load-Based Flexibility Needs						
Residual load	MWh	✓			✓	
Daily flexibility need	MWh	✓			✓	
Weekly flexibility need	MWh	✓			✓	
Seasonal flexibility need	MWh				✓	
Technology contributions to flexibility	MWh				✓	
Cross-border contributions to flexibility	MWh				✓	
Ramping Needs						
Maximum ramping requirement	MWh				✓	
Ramping shortfall indicator	MWh	✓			✓	
Short-Term Needs (Forecast Errors)						
Short-term need	MWh	✓		✓	✓	

Result	Units	Time series	Pre-optimisation	Monte Carlo	Monte Carlo	EVA
Short-term needs total and maximum/minimum	MWh			✓	✓	
Short-term shortfall curtailment	MWh	✓		✓	✓	
Short-term shortfall ENS	MWh	✓		✓	✓	
Short-term technology contributions	MWh	✓		✓	✓	
Short-term cross-border contributions	MWh	✓		✓	✓	
Curtailment Assessment						
VRE Curtailment	MWh	✓		✓	✓	
Curtailment Reduction through Dummy Storage	MW				✓	
Curtailment Reduction: Network Needs	MW	✓			✓	

3.5.2.4. Output file structure

The model outputs are stored in a NetCDF file (`model_outputs.nc`) using xarray DataTree format, located at `{output_dir}/{job_id}/results/assessment/model_outputs.nc`. The file contains two main groups organised by analysis type:

File Groups:

- `/base`: Main EVA results (55+ variables)
- `/dummy_storage_optimization`: Dummy storage optimisation results across multiple configurations (35+ variables)

Common Dimensions:

Dimension	Description
`TY`	Target year(s)

Dimension	Description
`CY`	Climate year(s)
`BZ`	Bidding zones
`carrier`	Technology/carrier types
`hour`	Hour of year (0-8759)
`day`	Day index
`week`	Week index
`iteration`	EVA iteration number
`bidding_zone`	Bidding zone names (for prices)
`generator`	Generator names (for reserves)
`asset`	Asset names (for NPV)

Base Group Variables by Category:

Flexibility Indicators (`kind="flexibility_indicator"`):

- `curtailment` (TY, CY, hour, carrier, BZ) - Renewable curtailment
- `curtailment_aggregated` (TY, CY, BZ, carrier) - Total curtailment by carrier
- `residual_load` (TY, CY, BZ, hour) - Load minus VRE generation
- `daily_flexibility_need` (TY, CY, BZ, day) - Daily flexibility requirement
- `daily_flexibility_need_aggregated` (TY, CY, BZ) - Total daily flexibility
- `weekly_flexibility_need` (TY, CY, BZ, week) - Weekly flexibility requirement
- `weekly_flexibility_need_aggregated` (TY, CY, BZ) - Total weekly flexibility
- `seasonal_flexibility_need` (TY, CY, BZ) - Seasonal flexibility requirement
- `maximum_ramping_requirement` (TY, CY, BZ) - Maximum hourly ramping
- `ramping_shortfall_upward` (TY, CY, hour, BZ) - Unmet upward ramping
- `ramping_shortfall_upward_aggregated` (TY, CY, BZ) - Total upward shortfall
- `ramping_shortfall_downward` (TY, CY, BZ, hour) - Unmet downward ramping
- `ramping_shortfall_downward_aggregated` (TY, CY, BZ) - Total downward shortfall
- `technology_contributions_daily/weekly/seasonal` (TY, CY, carrier, BZ)

- `cross_border_contributions_daily/weekly/seasonal` (TY, CY, BZ)
- `short_term_need_upward_hourly` (TY, CY, hour, BZ) - Hourly upward forecast errors
- `short_term_need_downward_hourly` (TY, CY, hour, BZ) - Hourly downward forecast errors
- `total_short_term_need_upward/downward` (TY, CY, BZ) - Total forecast errors

Market Outputs (`kind="market_output"`):

- `supply` (TY, CY, hour, carrier, BZ) - Energy supply timeseries
- `withdrawal` (TY, CY, hour, carrier, BZ) - Energy withdrawal timeseries
- `market_prices_day_ahead` (TY, CY, hour, bidding_zone) - DA prices [€/MWh]
- `market_prices_intraday` (TY, CY, hour, bidding_zone) - ID prices [€/MWh]
- `average_prices` (TY, CY, bidding_zone) - Time-averaged prices [€/MWh]
- `price_volatility` (TY, CY, bidding_zone) - Price standard deviation [€/MWh]
- `total_generation_day_ahead/intraday` (TY, CY, day, carrier, BZ) - Daily generation
- `reserve_capacity_day_ahead_r_FCR_up/down` (TY, CY, hour, generator) - FCR reserves
- `reserve_capacity_day_ahead_r_FRR_up/down` (TY, CY, hour, generator) - FRR reserves
- `demand` (TY, CY, hour, Load) - Base electrical demand
- `storage_units_charging` (TY, CY, hour, StorageUnit) - Storage charging
- `energy_not_served` (TY, CY, BZ, hour) - Load shedding per hour and zone [MWh]
- `total_energy_not_served` (TY, CY, BZ) - Total load shedding per zone [MWh]
- `loss_of_load` (TY, CY, BZ) - Number of hours with load shedding [h]

EVA Outputs (`kind="eva_output"`):

- `production_capacities` (TY, CY, carrier, BZ) - Installed generation capacity
- `storage_capacities` (TY, CY, carrier, BZ) - Installed storage capacity
- `commissioned_capacity` (TY, iteration, carrier, BZ) - Capacity additions per iteration
- `decommissioned_capacity` (TY, iteration, carrier, BZ) - Capacity removals per iteration
- `npv_per_mw` (TY, iteration, asset) - Net present value per MW [EUR/MW]

Note: The dummy storage optimisation group contains the same variables with additional dimensions `(mh, ct, ...)` for comparing across storage configurations and curtailment targets.

3.6. Advanced temporal clustering

3.6.1. Background

Each EVA iteration requires running the full day-ahead and intraday market simulations across all climate years (CYs) and forced-outage (FO) samples. With $|CY|$ climate years, $|OS|$ outage samples, and $|TY|$ target years, the number of market solves per iteration scales as $|TY| \times |CY| \times |OS|$. At the early stages of the capacity expansion loop, installed capacities change substantially between iterations and high accuracy is not yet required. Running the full set of market simulations at every iteration therefore represents unnecessary computational cost.

The observation that motivates clustering is that many weeks across different climate years share similar revenue patterns: weeks with similar levels of renewable generation, demand, and prices produce similar revenues per carrier and bidding zone. Such weeks are interchangeable for the purpose of estimating annual NPVs, and running only a representative subset suffices.

3.6.2. Target

Reduce the simulated time per EVA iteration from $|CY|$ full years per target year to k representative horizon chunks per target year, while preserving the accuracy of the NPV calculation to within an acceptable tolerance. For each target year, the horizon chunks of all climate years form one joint pool Q of $|Q| = |CY| \times H$ chunks, where H is the number of chunks per climate year, and this pool is clustered in a single pass. A clustered EVA iteration therefore solves k day-ahead and $k \times |OS|$ intraday market models per target year, regardless of the number of climate years. All k centroids may originate from a single climate year if the revenue data supports it – this is a valid outcome, not a defect. Full EVA iterations at regular intervals refresh the cluster assignments and correct any accumulated approximation error.

3.6.3. Implementation strategy

Full and clustered EVA iterations

In this section, an *iteration* is always an iteration it of the EVA loop of Section 3.4; clustering does not add a loop of its own. When clustering is enabled, each EVA iteration is either a full or a clustered EVA iteration:

- A **full EVA iteration** runs the day-ahead and intraday market models on the full year for all TY/CY/FO combinations, exactly as without clustering, and computes the NPVs from these full-year results. The horizon chunks are then (re)clustered on the full-year day-ahead results of this iteration. Clustering is therefore always based on full-year market simulations, not on the results of the storage or maintenance planning.

- A **clustered EVA iteration** runs the market models only on the k centroid chunks per target year, using the cluster assignments of the most recent full EVA iteration, and computes the NPVs from the centroid results. Storage planning still runs on the full year, and the capacity update and convergence check are the same as in a full EVA iteration.

The type of EVA iteration it is determined from the convergence status of iteration $it-1$:

$$mode_{\text{it}} = \begin{cases} \text{full} & \text{if } \neg enable \\ \text{full} & \text{if } it = 0 \\ \text{full} & \text{if } it \bmod freq = 0 \\ \text{full} & \text{if } it \geq max_iterations - 1 \\ \text{full} & \text{if } status_{\text{it}-1} = \texttt{ClusteredConverged} \\ \text{clustered} & \text{otherwise} \end{cases} \tag{15.1}$$

where $freq$ is the full-run frequency and $max_iterations$ is the maximum number of EVA iterations. The cases are evaluated in priority order:

- When clustering is disabled, all EVA iterations are full EVA iterations and the workflow is identical to the baseline with no clustering overhead.

- Iteration 0 is always a full EVA iteration, because the first clustering needs full-year market results.

- The fixed-frequency case ($it \bmod freq = 0$) refreshes the cluster assignments at regular intervals. With the default full-run frequency of 10, iterations 0, 10, 20, … are full EVA iterations, and the up to nine clustered EVA iterations in between reuse the clusters of the full EVA iteration that precedes them.

- The last-iteration case ($it \geq max_iterations - 1$) ensures that the final capacity update is always based on full-year market simulations, regardless of the schedule.

- The `ClusteredConverged` case provides a two-step convergence gate: if the convergence criterion is met in a clustered EVA iteration, the status is recorded as `ClusteredConverged` rather than `Converged`. The next iteration then runs as a full EVA iteration to validate the result; only if the criterion is also met there is the status `Converged` and the loop terminates. Otherwise, the loop continues with the schedule above.

Figure 16 shows how the clustering steps below fit into an EVA iteration.

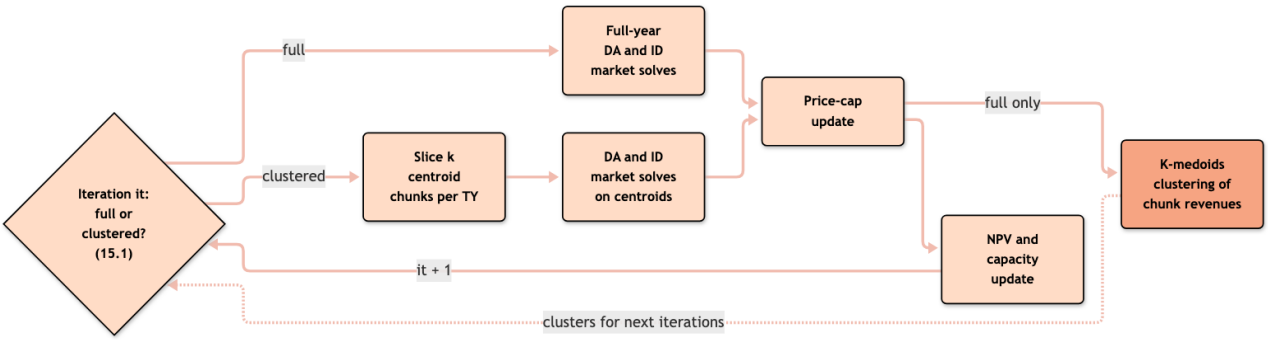


Figure 16: Advanced temporal clustering within the EVA loop. The clustering (dark) runs only in full EVA iterations, on their full-year day-ahead results; clustered EVA iterations solve only the centroid chunks.

Chunk extraction

The solved full-year day-ahead network of each TY/CY combination is sliced into non-overlapping horizon chunks of fixed length, controlled by the integer parameter `horizon_days`. Chunks slide from the first snapshot in steps of $\text{horizon_days} \times 24$ hours. Common values are:

`horizon_days`	Chunk length	Approximate chunks per CY
7	7 days (168 h)	52
14	14 days (336 h)	26
30	30 days (720 h)	12

Any positive integer is valid. Chunks do not require calendar alignment (e.g. Monday start), making this approach suitable for both full-year networks and short test prebuilts. A partial chunk at the end of the year is discarded. For each chunk q belonging to climate year cy and target year ty, the chunk is uniquely identified by its target year, climate year, and temporal position, and its bounding timestamps are recorded.

Revenue features

For each chunk q, the energy revenue is computed per bidding zone n and carrier c by evaluating the PyPSA statistics on the network restricted to the chunk's snapshots, using the day-ahead prices after the price-cap update:

$$R_{q,n,c} = \sum_{t \in T_q} \sum_{s \in S_{n,c}} \lambda^{\mathrm{DA}}_{n,t} \, g^{\mathrm{DA}}_{n,s,t} \quad \forall q \in Q,\ \forall n \in N,\ \forall c \in C \tag{15.2}$$

where T_q is the set of snapshots belonging to chunk q, C is the set of carriers (e.g., CCGT, wind, battery), and $S_{n,c}$ is the set of generators and storage units with carrier c at bidding zone n; for storage units, $g^{\mathrm{DA}}_{n,s,t}$ is the net dispatch. For a given (ty, cy) combination, this yields a feature matrix $\mathbf{R}_{\mathrm{cy}} \in \mathbb{R}^{H \times (|N| \cdot |C|)}$. BZ-carrier combinations for which no generators or storage units exist are

naturally absent from the matrix, keeping effective dimensionality lower than $|N| \cdot |C|$. The per-CY matrices of a target year are concatenated to form the joint pool Q for clustering.

Normalisation

Each BZ-carrier column is standardised to zero mean and unit variance before clustering:

$$\tilde{R}_{q,n,c} = \frac{R_{q,n,c} - \mu_{n,c}}{\sigma_{n,c}} \quad \forall q \in Q,\ \forall n \in N,\ \forall c \in C \tag{15.3}$$

where $\mu_{n,c}$ and $\sigma_{n,c}$ are the sample mean and standard deviation of BZ-carrier feature (n, c) across all chunks of the joint pool. This gives each BZ-carrier combination equal weight in the distance metric, protecting small or peripheral bidding zones (e.g., Malta, Cyprus, Ireland) from being dominated by the larger continental zones with higher absolute revenues.

K-medoids clustering

K-medoids clustering is performed only in full EVA iterations, separately for each target year. Clustered EVA iterations reuse the cluster assignments of the most recent full EVA iteration instead of re-clustering. This "cluster freeze" keeps the centroids fixed between full EVA iterations and avoids the expense of re-clustering in every iteration.

In a full EVA iteration, the normalised feature matrix $\tilde{\mathbf{R}} \in \mathbb{R}^{|Q| \times (|N| \cdot |C|)}$, formed by concatenating the chunk rows of all CYs of the target year, is clustered jointly into k groups using the FasterPAM K-medoids algorithm (Schubert & Rousseeuw 2021). The algorithm minimises the sum of Euclidean distances from each chunk's BZ-carrier revenue vector to its cluster medoid across the full joint pool:

$$\min_{\{C_1,\ldots,C_k\}} \sum_{\kappa=1}^{k} \sum_{q \in C_\kappa} \left\| \tilde{\mathbf{R}}_q - \tilde{\mathbf{R}}_{q^*_\kappa} \right\|_2 \tag{15.4}$$

where $\tilde{\mathbf{R}}_q \in \mathbb{R}^{|N| \cdot |C|}$ is the flattened BZ-carrier feature vector for chunk q, C_κ is the set of chunks assigned to cluster κ across all CYs, and $q^*_\kappa \in C_\kappa$ is the medoid of cluster κ – the chunk that minimises the total distance to all other members of the cluster. Because the medoid is a real element of the data, the centroid chunk is always an actual simulated period rather than a synthetic average. The climate year of each centroid is read from the medoid's metadata; it is metadata, not a dimension of the expansion.

Clustering determines **representation**, not **coverage**: with $k = 4$ and $|CY| = 2$, it is valid for all 4 centroids to originate from one climate year if that CY's revenue patterns are the most representative of the joint pool. No minimum per-CY centroid count is enforced.

The clustering step records whether it performed fresh clustering or reused previous assignments, along with the resulting centroid identifiers.

Cluster weights

The weight of cluster κ is the fraction of the joint chunk pool of the target year that it represents:

$$w_\kappa = \frac{|C_\kappa|}{|Q|} \quad \forall \kappa \in \{1, \ldots, k\} \tag{15.5}$$

The weights are normalised by construction:

$$\sum_{\kappa=1}^{k} w_\kappa = 1 \tag{15.6}$$

Centroid networks

In a clustered EVA iteration, the snapshots of each medoid chunk are extracted from the unsolved base networks of the iteration, both forecast (for the day-ahead model) and actual (for the intraday model), and the snapshot weightings are scaled to represent the cluster weight:

$$snapshot_weightings_t = w_\kappa \cdot \frac{N_{\text{year}}}{N_{\text{chunk}}} \quad \forall t \in T_{q^*_\kappa} \tag{15.7}$$

where N_{year} is the number of snapshots of the full-year network (8760 at hourly resolution) and N_{chunk} is the number of snapshots of the chunk (e.g. 168). Together, the k centroid networks of a target year thus represent one year. Static properties, including bidding zone definitions and component capacities, are preserved unchanged.

Centroid market solves

The day-ahead and intraday market models are solved *only* on the k centroid networks per target year: k day-ahead solves and, for each forced-outage sample, k intraday solves. The day-ahead and intraday models of a centroid cover the same chronological chunk, because the intraday model takes over the day-ahead commitments of that chunk. The day-ahead model solves a linearised unit commitment formulation in most configurations (not necessarily a full MILP), and the intraday model solves a linear economic dispatch. The storage plans from the Storage Planning step (which remains the same, solved for the full year) set the initial and ending boundary conditions of storage units within each centroid chunk. Because the k centroid networks are independent of one another, they can be solved in parallel, yielding a significant runtime reduction compared to the sequential full-year solves of a full EVA iteration.

Price-cap update and NPV (centroid-only, no full-year reconstruction)

In clustered EVA iterations, full-year PyPSA networks are never reconstructed. Solved centroid networks are not tiled back to disk as full-year files. All downstream processing operates directly on the k centroid networks. The only quantities reconstructed to a full-year timeline are: (a) the price-cap time series, as a lightweight CSV mapping centroid cap values to all assigned non-centroid chunks; and (b) per-CY revenues and expenses, accumulated from the centroid results for the NPV computation.

Regulatory price-cap update. Centroid networks are grouped by climate year. For each group, marginal prices from all centroids are concatenated in chronological order and HMMCP detection is run on the combined timeline. Updated price-cap values are applied back to each centroid network. A full-year price-cap time series is then reconstructed by mapping centroid price-cap

values back to every assigned non-centroid chunk. This series is used by downstream capacity-expansion rules.

NPV calculation. The NPV step operates directly on the k centroid day-ahead and intraday market results. Let X_κ be a revenue or variable cost of an asset over the centroid chunk of cluster κ (unscaled, i.e. without the snapshot weighting of (15.7)), and H_{cy} the number of chunks of climate year cy. The annual value for climate year cy is accumulated as

$$X_{\mathrm{cy}} = \sum_{\kappa=1}^{k} |C_\kappa \cap Q_{\mathrm{cy}}| \, X_\kappa \tag{15.8}$$

where $Q_{\mathrm{cy}} \subseteq Q$ is the set of chunks of climate year cy, so that each centroid stands in for every chunk of its cluster in that climate year. Annual fixed costs and exogenous revenues are distributed with the fractions $|C_\kappa \cap Q_{\mathrm{cy}}|/H_{\mathrm{cy}}$, which sum to one over the clusters, so that each climate year carries them once.

Storage planning and SOC boundary conditions

The integration of storage planning with advanced temporal clustering is governed by the following design decisions:

- **Storage planning always runs on the full year.** The pre-optimisation always runs per (ty, cy) on the full-year resampled network regardless of the type of EVA iteration, producing hourly SOC targets for hydro storage.
- **Centroid networks are sliced from unsolved base networks.** In a clustered EVA iteration, the unsolved base networks for the medoid chunks are extracted before the market solve.
- **SOC initialisation from storage plan.** For the first rolling-horizon window of each centroid solve, hydro storage units are initialised from the storage plan at the timestamp immediately preceding the centroid window start. This gives each centroid a realistic hydro SOC consistent with where the reservoir would be at that point in the year. Battery and DSR units retain their default initial SOC.
- **SOC independence between centroids.** The k centroid networks are solved independently. The ending SOC of centroid κ does not serve as the initial SOC of centroid $\kappa + 1$. Because centroids represent distinct, non-sequential weather/revenue patterns, imposing chronological SOC continuity between them would be mathematically incorrect.

4. Data management

4.1. Input data

The model reads each combination of TY and CY from a pre-built network: a PyPSA network file holding all components of the power system with their technical and economic attributes and their time series. Preparing the pre-built networks is not part of the model, and the model does not fetch any data at run time. Besides the pre-built networks, the model takes the following inputs, as shown in **Figure 17**:

- **Configuration.** The run is controlled by a configuration file (see Section 2.2 System configuration).
- **Day-ahead forecasts (optional).** By default, the day-ahead forecasts of demand and renewable generation are derived by adding synthetic forecast errors to the actual time series. Alternatively, forecast time series can be supplied as CSV files.
- **Flow-based domains (optional).** When interconnection is modelled with FBMC (see Section 3.1.5 Network graph and transmission), the flow-based domains are read from CSV files.
- **Edited networks (optional).** In sensitivity mode, the model reads networks that have been exported as PyPSA component CSV files and edited by the user, instead of the pre-built networks.

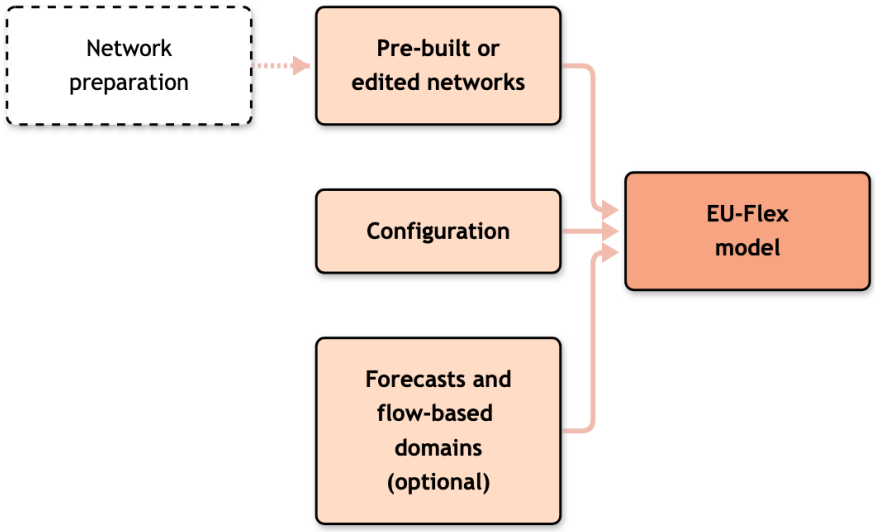


Figure 17: Inputs to the EU-Flex model. Network preparation (dashed) is not part of the model.

Table 6 lists the main input data and where it is held. All of it is given per TY and CY, and time series have the time resolution of the pre-built network. Appendix 6.2 Detailed data inventory lists the attributes of each component type; see also the PyPSA documentation[38].

Table 6: Overview of the main input data

Item	Held in	Used in
Electricity demand	Loads (time series)	Storage planning, maintenance planning, market simulation
VRE generation	Generators (availability time series)	Storage planning, maintenance planning, market simulation
Day-ahead forecasts of demand and VRE	Derived from the actual time series, or forecast CSV files	Market simulation (DA-UCED)
Generator parameters	Generators	Maintenance planning, market simulation, EVA
Storage parameters	Storage units	Storage planning, market simulation, EVA
Flexible demand	Generators and storage units	Market simulation, EVA
Hydro inflows	Storage units (time series)	Storage planning, maintenance planning, market simulation
Planned outage rates	Generators	Maintenance planning
Forced outage rates	Generators	Monte Carlo sampling of forced outages for market simulation (ID-ED)
Investment parameters	Generators and storage units	EVA
Bidding zones	Buses	All steps
Interconnections and NTCs	Links (capacities and time series)	Market simulation
Flow-based domains (CNECs, PTDFs and RAMs)	Flow-based domain CSV files	Market simulation

4.2. Data quality controls

Errors in the input data, such as missing values or implausible parameters, can make the market simulations infeasible or distort their results. The model therefore checks its inputs before running any simulations, as summarised in Table 7. Errors stop the run with a message naming the offending entries, and corrections are logged.

Table 7: Overview of input data checks

Check	When	Action if a problem is found
Configuration against its schema	At start-up	Stop the run
Presence of the input files	At start-up	Stop the run
Generator and storage unit attributes: types, value ranges and consistency between attributes	Base network build	Fill in missing attributes with defaults and check again, and stop the run if the check still fails. In sensitivity mode, stop the run without filling in defaults
Inconsistent operating limits, e.g. a minimum output above the maximum	Base network build	Correct the values and log the correction

5. Testing and validation

5.1. Background

A well-defined testing and validation strategy is essential for ensuring that an energy systems model is both robust and reliable for decision-making. Given the novelty of the EVA methodology and the limited availability of direct benchmarks, validation is not merely a matter of comparing outputs to a single expected value. Instead, it necessitates an iterative approach to assessing whether the model behaves consistently across a range of scenarios.

During the development phase, a structured testing framework is crucial to confirm that the model performs as expected. This strategy should include both unit testing to verify the accuracy of individual components and system-level validation to ensure that the model as a whole produces results that align with real-world expectations. By integrating these approaches, the testing process can identify inconsistencies, enhance model reliability, and build confidence in its decision-support capabilities.

The requirement for non-functional testing such as performance and security testing is outside the scope of this document. Checks of the input data are covered in Section 4.2 Data quality controls. Accordingly, this section presents a brief summary of validation of outputs from the EU-Flex model only, or functional requirement testing.

5.2. Target

Create a standardised collection of test scenarios that demonstrate how input changes produce expected outputs. The proposed test scenarios are based on the best available knowledge of this model during the specification's development, though the chosen scenarios may require modifications or expansions. Standard tests are executed as features are integrated into the model. The test cases, which are set up in snakemake, are run regularly as the model is developed.

5.3. Implementation strategy

The general approach for validation of model outputs is inspired by the academic literature[43], albeit extended to account for the requirements of the EU-Flex model. The general procedure for model validation has three main parts, detailed below.

Step 1: Baseline Validation

Firstly, **baseline validation** uses a set of simple validation cases, developed in collaboration with ACER, to test the workflow and make sure the model performs as expected as different features are developed. These test cases are simplified compared to the full EU-Flex model (e.g. two countries, short planning horizon, two CYs, two TYs), and include an isolated bidding zone test. They cover all the main functionalities and components but are of much smaller dimensionality compared to the full model, allowing for a quick initial validation. The baseline validation step includes a number of automated modular tests:

- Unit tests are used to ensure individual functions and components are behaving as expected.
- Integration tests look at the functionality in the full system, and interactions among components.
- Regression tests assess whether any new changes break existing functionality. Thus, while unit tests focus on individual components or functions of the model in isolation tests, regression tests assess the functionality of the entire model to detect unintended changes in behaviour due to code updates.
- Performance tests are used to evaluate any potential performance degradation resulting from the implementation of a new feature, both for smaller test cases and the full scale model.

Step 2: Historical and Dynamic Validation

The second step is **historical validation**, which is based on a set of historical observations and datasets, requires full-scale model runs, and focuses on market outputs and reserves. It assesses whether the model accurately reproduces realistic energy system behaviour, with a particular focus on flexibility assessment metrics. The extent of this validation step depends on data and resource availability; the datasets considered are summarised in Table 8 below. Note that where the source listed is “ACER”, the implication is that confidential data may be integrated for that category. The most valuable validation in this step is to reproduce ERAA 2023 as closely as possible using its input datasets, aiming at consistency in capacity expansion and adequacy indicators. The requirements and extent of this step are agreed with ACER.

Table 8: Test data specification for historical validation step

Category	Datasets	Source
Timeseries	Historical generation and demand forecast errors	ENTSO-E Transparency
Reserves	Historical reserve procurement and requirements (FCR, FRR), reserve providers	ENTSO-E Transparency
Market	Historical day-ahead and real time electricity prices, reserve prices	ENTSO-E Transparency + OpenMeteo + ACER

Category	Datasets	Source
Network Flows	Historical cross-border trade volumes	ENTSO-E Transparency
Flexibility Metrics	Historical and projected flexibility metrics per TY and CY	ERAA 2024
EVA	Projected capacity mix per TY	ERAA 2024

Alongside historical validation, **dynamic validation** is performed. This step focuses on edge cases, where extreme variations in inputs are expected to produce specific and predictable outputs. Given that the EU-Flex model models are linear, sensitivities to changes in inputs should directly correlate with outputs. For example, decreasing marginal costs should never increase the market model's objective function, while lowering investment costs should never result in reduced installed capacity for a technology. Some of these checks are already part of the baseline validation step described above; Step 2 extends them to ensure the model logic is working as expected.

This is an iterative process, ensuring that extreme input variations yield the expected outcomes. The metrics assessed are refined through stakeholder engagement and expert consultation, to establish a comprehensive and robust validation approach for EU-Flex modelling results. Given the extensive list of possible dynamic validation tests, the validation focuses on a selection of them. These tests are performed by combining the `sensitivity` mode with detailed analysis and comparison of outputs; where a test is automated, it runs independently as a snakemake workflow, allowing for a modular and structured validation process.

Step 3: Expert Validation

Finally, **expert validation** is used to verify final model results. The final step involves allowing experts from different disciplines within energy systems to look at the full model, from the codebase to the inputs to the outputs. The expert judgement can then be used to complete a final validation of results, or explain why any potential differences may arise.

The expert validation step is largely based on the same datasets detailed above for Step 2. The only difference may be the integration of confidential datasets from ACER, which is decided case by case, given the priority to make sure confidentiality of sensitive information is maintained. Furthermore, there may be limited value to an in-depth expert validation if domain practitioners are unable to access the full set of inputs for the model - and consequently identify any potential discrepancies between inputs and outputs.

Workshops with the expert groups are organised to validate the methodology and the model results.

6. Appendix

6.1. Detailed flow chart

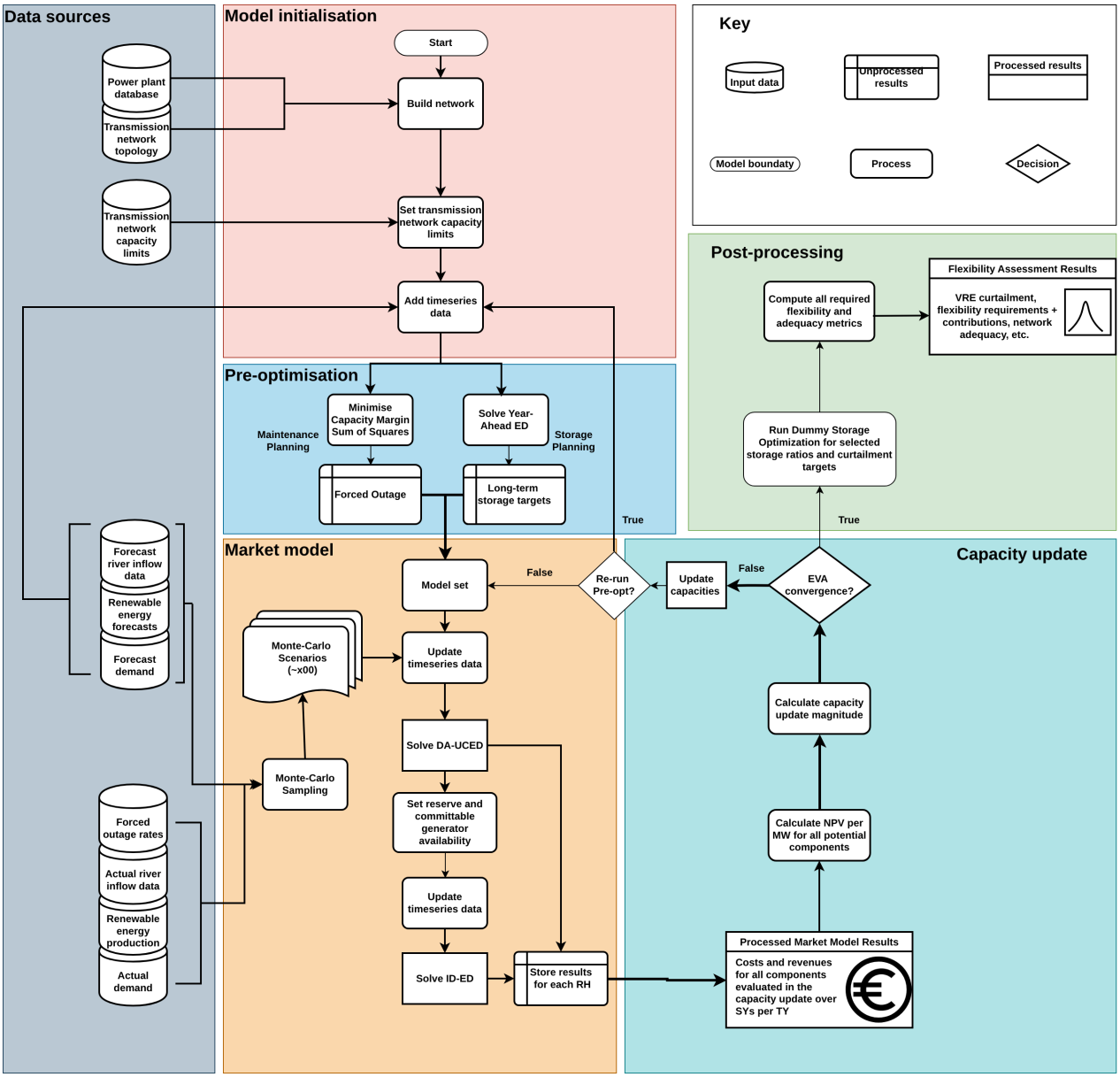


Figure 18: Detailed overview of the proposed workflow for the EU-Flex model.

6.2. Detailed data inventory

The tables below outline the input data used in the models within the EU-Flex model. Note that not all the parameters are mandatory inputs, some of them are only required for a subset of components, or can be seen as optional features. This list, though not exhaustive, is structured based on PyPSA components. For a comprehensive overview of PyPSA components and associated data, please refer to: https://pypsa.readthedocs.io/en/latest/user-guide/components.html

Table 9: Generator input parameters

Item	Attribute	Type	Unit	Description
Generator	name	string	n/a	Unique name
Generator	bus	string	n/a	name of bus to which generator is attached
Generator	p_nom	float	MW	Nominal power for limits in optimisation.
Generator	p_nom_min	float	MW	If p_nom is extendable in optimisation, set its minimum value.
Generator	p_nom_max	float	MW	If p_nom is extendable in optimisation, set its maximum value (e.g. limited by technical potential).
Generator	p_min_pu	static or series	per unit	The minimum output for each snapshot per unit of p_nom for the optimisation (e.g. for variable renewable generators this can change due to weather conditions and compulsory feed-in; for conventional generators it represents a minimal dispatch). Note that if committable is False and p_min_pu > 0, this represents a must-run condition.

Item	Attribute	Type	Unit	Description
Generator	p_max_pu	static or series	per unit	The maximum output for each snapshot per unit of p_nom for the optimisation (e.g. for variable renewable generators this can change due to weather conditions; for conventional generators it represents a maximum dispatch).
Generator	p_set	static or series	MW	active power set point (for PF)
Generator	sign	float	n/a	power sign
Generator	carrier	string	n/a	Prime mover energy carrier (e.g. coal, gas, wind, solar); required for global constraints on primary energy in optimisation
Generator	marginal_cost	static or series	currency/MWh	Marginal cost of production of 1 MWh.
Generator	active	boolean	n/a	Whether to consider the component in basic functionality or not
Generator	build_year	int	year	build year
Generator	lifetime	float	years	lifetime
Generator	capital_cost	float	currency/MW	Fixed period costs of extending p_nom by 1 MW, including periodised investment costs and periodic fixed O&M costs (e.g. annuitised investment costs).
Generator	efficiency	static or series	per unit	Ratio between primary energy and electrical energy, e.g. takes value 0.4 MWh_elec/MWh_thermal for gas. This is required for global constraints on primary energy in optimisation.
Generator	committable	boolean	n/a	Use unit commitment (only possible if p_nom is not extendable).

Item	Attribute	Type	Unit	Description
Generator	start_up_cost	float	currency	Cost to start up the generator. Only read if committable is True.
Generator	shut_down_cost	float	currency	Cost to shut down the generator. Only read if committable is True.
Generator	stand_by_cost	static or series	currency/h	Stand-by cost for operating the generator at null power output.
Generator	min_up_time	int	snapshots	Minimum number of snapshots for status to be 1. Only read if committable is True.
Generator	min_down_time	int	snapshots	Minimum number of snapshots for status to be 0. Only read if committable is True.
Generator	up_time_before	int	snapshots	Number of snapshots that the generator was online before network.snapshots start. Only read if committable is True and min_up_time is non-zero.
Generator	down_time_before	int	snapshots	Number of snapshots that the generator was offline before network.snapshots start. Only read if committable is True and min_down_time is non-zero.
Generator	ramp_limit_up	static or series	per unit	Maximum active power increase from one snapshot to the next, per unit of the nominal power. Ignored if NaN.
Generator	ramp_limit_down	static or series	per unit	Maximum active power decrease from one snapshot to the next, per unit of the nominal power. Ignored if NaN.
Generator	ramp_limit_start_up	float	per unit	Maximum active power increase at start up, per unit of the nominal power. Only read if committable is True.

Item	Attribute	Type	Unit	Description
Generator	ramp_limit_shut_down	float	per unit	Maximum active power decrease at shut down, per unit of the nominal power. Only read if committable is True.
Generator	weight	float	n/a	Weighting of a generator. Only used for network clustering.
Generator	Planned outage rate	float	per unit	Gives percentage of days per year a generator is out for planned maintenance.

Table 10: Buses input parameters

Item	Attribute	Type	Unit	Description
Bus	name	string	n/a	Unique name
Bus	x	float	n/a	Position (e.g. longitude); the Spatial Reference System Identifier (SRID) is set in network.srid.
Bus	y	float	n/a	Position (e.g. latitude); the Spatial Reference System Identifier (SRID) is set in network.srid.
Bus	carrier	string	n/a	Energy carrier: can be “AC” or “DC” for electrical buses, or “heat” or “gas”.
Bus	unit	string	n/a	Unit of the bus carrier if the implicitly assumed unit (“MW”) is inappropriate (e.g. “t/h”, “MWh_th/h”). Only descriptive. Does not influence any PyPSA functions.

Table 11: Carrier input parameters

Item	Attribute	Type	Unit	Description
Carrier	name	string	n/a	Unique name

Item	Attribute	Type	Unit	Description
Carrier	co2_emissions	float	tonnes/MWh	Emissions in CO2-tonnes-equivalent per MWh of primary energy (e.g. methane has 0.2 tonnes_CO2/ MWh_thermal).
Carrier	color	string	n/a	plotting colour
Carrier	nice_name	string	n/a	More precise descriptive name

Table 12: Links parameters

Item	Attribute	Type	Unit	Description
Links	name	string	n/a	Unique name
Links	bus0	string	n/a	Name of first bus to which link is attached.
Links	bus1	string	n/a	Name of other bus to which link is attached.
Links	carrier	string	n/a	Energy carrier transported by the link: can be “DC” for electrical HVDC links, or “heat” or “gas” etc.
Links	efficiency	static or series	per unit	Efficiency of power transfer from bus0 to bus1. (Can be time-dependent to represent temperature-dependent Coefficient of Performance of a heat pump from an electric to a heat bus.)
Links	active	boolean	n/a	Whether to consider the component in basic functionality or not
Links	build_year	int	year	build year
Links	lifetime	float	years	lifetime
Links	p_nom	float	MW	Limit of active power which can pass through link.
Links	p_nom_min	float	MW	If p_nom is extendable, set its minimum value.

Item	Attribute	Type	Unit	Description
Links	p_nom_max	float	MW	If p_nom is extendable, set its maximum value (e.g. limited by potential).
Links	p_set	static or series	MW	The dispatch set point for p0 of the link in PF.
Links	p_min_pu	static or series	per unit of p_nom	Minimal dispatch (can also be negative) per unit of p_nom for the link.
Links	p_max_pu	static or series	per unit of p_nom	Maximal dispatch (can also be negative) per unit of p_nom for the link.
Links	capital_cost	float	currency/MW	Fixed period costs of extending p_nom by 1 MW, including periodised investment costs and periodic fixed O&M costs (e.g. annuitised investment costs).
Links	marginal_cost	static or series	currency/MWh	Marginal cost of transferring 1 MWh (before efficiency losses) from bus0 to bus1. NB: marginal cost only makes sense if p_max_pu >= 0.

Table 13: Loads parameters

Item	Attribute	Type	Unit	Description
Loads	name	string	n/a	Unique name
Loads	bus	string	n/a	Name of bus to which load is attached.
Loads	carrier	string	n/a	Energy carrier: can be “AC” or “DC” for electrical buses, or “heat” or “gas”.
Loads	p_set	static or series	MW	Active power consumption (positive if the load is consuming power).
Loads	sign	float	n/a	power sign (opposite sign to generator)

Table 14: Networks parameters

Item	Attribute	Type	Unit	Description
Networks	name	string	n/a	Unique name
Networks	snapshots	list or pandas.Index	n/a	List of snapshots or time steps. All time-dependent series quantities are indexed by ``network.snapshots``. To reset the snapshots, call ``network.set_snapshots(new)``.
Networks	snapshot_weightings	pandas.DataFrame	hours	The weightings applied to each snapshot, so that snapshots can represent more than one hour or fractions of one hour. The objective weightings are used to weight snapshots in the LOPF objective function. The store weightings determine the state of charge change for stores and storage units. The generator weightings are used when calculating global constraints.

Table 15: Storage units parameters

Item	Attribute	Type	Unit	Description
Storage Units	name	string	n/a	Unique name
Storage Units	bus	string	n/a	Name of bus to which storage unit is attached.
Storage Units	p_nom	float	MW	Nominal power for limits in OPF.
Storage Units	p_nom_min	float	MW	If p_nom is extendable in OPF, set its minimum value.
Storage Units	p_nom_max	float	MW	If p_nom is extendable in OPF, set its maximum value (e.g. limited by potential).

Item	Attribute	Type	Unit	Description
Storage Units	p_min_pu	static or series	per unit	The minimum output for each snapshot per unit of p_nom for the OPF (negative sign implies storing mode withdrawing power from bus).
Storage Units	p_max_pu	static or series	per unit	The maximum output for each snapshot per unit of p_nom for the OPF.
Storage Units	p_set	static or series	MW	active power set point (for PF)
Storage Units	sign	float	n/a	power sign
Storage Units	carrier	string	n/a	Prime mover energy carrier (e.g. coal, gas, wind, solar); required for global constraints on primary energy in OPF
Storage Units	spill_cost	static or series	currency/MWh	Cost of spilling 1 MWh.
Storage Units	marginal_cost	static or series	currency/MWh	Marginal cost of production of 1 MWh.
Storage Units	marginal_cost_storage	static or series	currency/MWh/h	Marginal cost of energy storage of 1 MWh for one hour.
Storage Units	capital_cost	float	currency/MW	Fixed period costs of extending p_nom by 1 MW, including periodised investment costs and periodic fixed O&M costs (e.g. annuitised investment costs).
Storage Units	active	boolean	n/a	Whether to consider the component in basic functionality or not
Storage Units	build_year	int	year	build year
Storage Units	lifetime	float	years	lifetime
Storage Units	state_of_charge_initial	float	MWh	State of charge before the snapshots in the OPF.
Storage Units	state_of_charge_set	static or series	MWh	State of charge set points for snapshots in the OPF.

Item	Attribute	Type	Unit	Description
Storage Units	cyclic_state_of_charge	boolean	n/a	Switch: if True, then state_of_charge_initial is ignored and the initial state of charge is set to the final state of charge for the group of snapshots in the OPF (soc[-1] = soc[len(snapshots)-1]).
Storage Units	max_hours	float	hours	Maximum state of charge capacity in terms of hours at full output capacity p_nom
Storage Units	efficiency_store	static or series	per unit	Efficiency of storage on the way into the storage.
Storage Units	efficiency_dispatch	static or series	per unit	Efficiency of storage on the way out of the storage.
Storage Units	standing_loss	static or series	per unit	Losses per hour to state of charge.
Storage Units	inflow	static or series	MW	Inflow to the state of charge, e.g. due to river inflow in the hydro reservoir.

Table 16: Store units parameters

Item	Attribute	Type	Unit	Description
Stores	name	string	n/a	Unique name
Stores	bus	string	n/a	Name of bus to which store is attached.
Stores	carrier	string	n/a	Energy carrier of the Store, e.g. “heat” or “gas”.
Stores	e_nom	float	MWh	Nominal energy capacity.
Stores	e_nom_extendable	boolean	n/a	Switch to allow capacity e_nom to be extended in OPF.
Stores	e_nom_min	float	MWh	If e_nom is extendable in OPF, set its minimum value.

Item	Attribute	Type	Unit	Description
Stores	e_nom_max	float	MWh	If e_nom is extendable in OPF, set its maximum value (e.g. limited by technical potential).
Stores	e_min_pu	static or series	per unit	Minimal value of e relative to e_nom for the OPF.
Stores	e_max_pu	static or series	per unit	Maximal value of e relative to e_nom for the OPF.
Stores	e_initial	float	MWh	Energy before the snapshots in the OPF.
Stores	e_cyclic	boolean	n/a	Switch: if True, then e_initial is ignored and the initial energy is set to the final energy for the group of snapshots in the OPF.
Stores	p_set	static or series	MW	active power set point (for PF)
Stores	marginal_cost	static or series	currency/MWh	Marginal cost applied to both charging and discharging of 1 MWh.
Stores	capital_cost	float	currency/MWh	Fixed period costs of extending e_nom by 1 MWh, including periodised investment costs and periodic fixed O&M costs (e.g. annuitised investment costs).
Stores	standing_loss	static or series	per unit	Losses per hour to energy.
Stores	active	boolean	n/a	Whether to consider the component in basic functionality or not
Stores	build_year	int	year	build year
Stores	lifetime	float	years	lifetime

[1]
The designation is without prejudice to positions on status, and in line with UNSCR 1244 and the ICJ Opinion on the Kosovo declaration of independence.

[2]
https://www.entsoe.eu/data/energy-identification-codes-eic/eic-approved-codes/

[3]
Bergh et al. (2016), The Flow-Based Market Coupling in Central Western Europe: Concepts and definitions. https://www.sciencedirect.com/science/article/abs/pii/S104061901530004X

[4]
https://www.entsoe.eu/outlooks/eraa/2023/report/ERAA_2023_Annex_2_Methodology.pdf

[5]
Note that in FBMC, a CNEC does not necessarily or explicitly establish a direct connection between two bidding zones.

[6] (1,2)
https://eepublicdownloads.blob.core.windows.net/public-cdn-container/clean-documents/sdc-documents/ERAA/ERAA_2024/FB%20domains.zip

[7]
https://www.entsoe.eu/outlooks/eraa/2023/report/ERAA_2023_Annex_2_Methodology.pdf

[9]
Other non-renewables include: Heavy oil, Light oil, Shale oil, Other

[10]
Other renewables includes: Geothermal, Marine, Small biomass, Waste. Power plant types such as (green) hydrogen could also be represented as generators.

[11]
Standing losses in storage systems represent energy lost while remaining in storage over time. These losses can take various forms, such as thermal dissipation in thermal storage, evaporation in hydro reservoirs, or electrical losses in batteries.

[14]
https://eepublicdownloads.entsoe.eu/clean-documents/sdc-documents/MAF/2020/Hydropower_Modelling_New_database_and_methodology_V1_0.pdf

[15]
Storage capacity is defined here as Reservoir Capacity / Net Generating Capacity.

[17]
https://www.entsoe.eu/outlooks/eraa/2023/report/ERAA_2023_Annex_2_Methodology.pdf

[18]
https://www.sciencedirect.com/science/article/pii/S014206151730457X#b0140

[19]
https://www.sciencedirect.com/science/article/pii/S0142061513001786

[20]

http://sciencedirect.com/science/article/pii/S0378779611000253

[21]
Taylor, J.A., 2015. Convex optimization of power systems. Cambridge University Press.

[46]
https://ieeexplore.ieee.org/document/8000610

[47]
https://www.acer.europa.eu/sites/default/files/documents/Other%20Documents/HMMCP_PPT.pdf

[23]
Exogenous revenue streams can be heating revenues, extra capacity mechanism revenues, among others. It can be used to, for instance, exclude some resources used in capacity mechanisms from being decommissioned in the EVA process.

[24]
Not all solvers report shadow values for mixed-integer problems. If such a solver (e.g., Gurobi) is used, it is necessary to perform a fixed model run, in which all the integer variables are fixed to their optimal levels, and the resulting LP is solved to obtain shadow values.

[25]
Indexes for rolling horizon (ro), target years (ty) and scenarios (sy) are omitted for clarity in notation. In the formulas, the sums over t span all time steps across all rolling horizons, ensuring a complete calculation of revenues and costs for a given ty within a specific sy.

[26]
Note that, in case there is a loss-of-load in the bidding zone, the market price reaches VoLL. As such, VoLL should be aligned/represent the market price cap.

[27]
Note that at this point, we add indices for scenarios and target years, which have so far been omitted for legibility reasons.

[28]
Note that this is not a standard NPV calculation but rather an indicator of NPV per unit of generator capacity. For simplicity, the notation still refers to it as NPV.

[31]
Also referred to as the Economic Viability Assessment (EVA) module

[33]
European Commission. (2019). *Study on flexibility markets: Final report.* https://op.europa.eu/en/publication-detail/-/publication/e6589254-a386-11e9-9d01-01aa75ed71a1/language-en

[34]

We note that insufficient ramping capabilities leading to lost load are evaluated using the ramping shortfall indicator.

[48]
The dummy storage optimisation minimises system cost by default (`eva.dummy_storage_optimization.minimize_system_costs`). The ACER Paper configurations include the dummy storage optimisation and use capacity minimisation instead (`minimize_system_costs: false`).

[38]
https://pypsa.readthedocs.io/en/latest/user-guide/components.html

[43]
https://www.sciencedirect.com/science/article/pii/S0142061520309534

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