METIS Technical Note T2

METIS Power Market Models

METIS Technical Notes
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1. INTRODUCTION

METIS is an on-going project[1] initiated by DG ENER for the development of an energy modelling software, with the aim to further support DG ENER's evidence-based policy making, especially in the areas of electricity and gas. The software is developed by Artelys with the support of IAEW (RWTH Aachen University), ConGas and Frontier Economics as part of Horizons 2020 and is closely followed by DG ENER. Two versions have been already delivered at the DG ENER premises.

The intention is to provide DG ENER with an in-house tool that can quickly provide insights and robust answers to complex economic and energy related questions, focusing on the short-term operation of the energy system and markets. METIS was used, along with PRIMES, in the impact assessment of the Market Design Initiative.

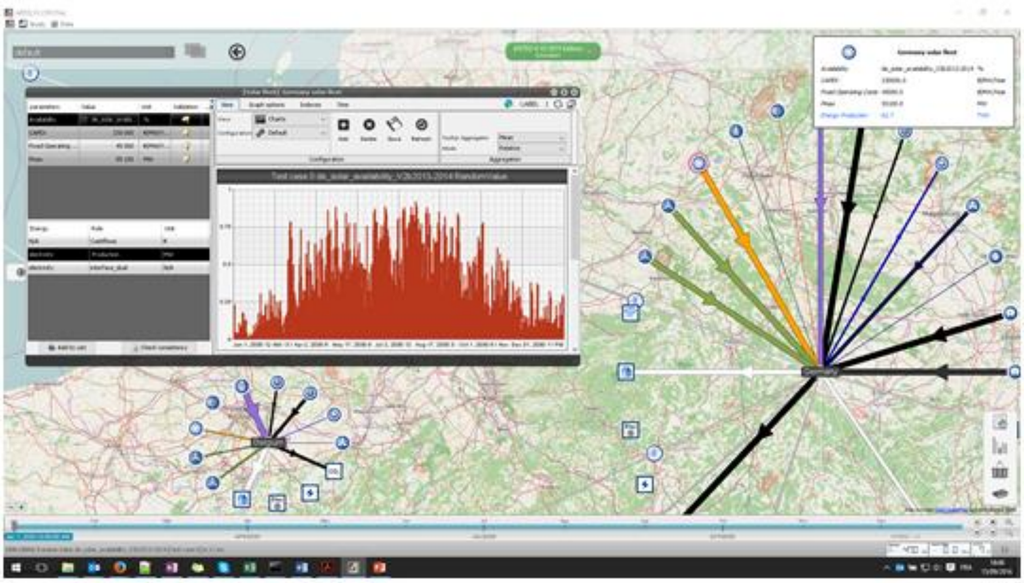


Figure 1 : Snapshot from METIS user interface screen

This document presents the main assumptions used for METIS power market module. After a quick overview of METIS main characteristics in Section 0, Section **Error! Reference source not found.** describes how energy assets are modelled, with a particular focus on reserve procurement. Section 3 describes the main methodology used for day-ahead and intraday market modelling, then Section 0 focuses on the balancing market.

[1] http://ec.europa.eu/dgs/energy/tenders/doc/2014/2014s_152_272370_specifications.pdf

2. METIS MAIN CHARACTERISTICS

2.1. OVERALL DESCRIPTION

METIS works complementary to long-term energy system models (like PRIMES from NTUA and POTEnCIA from JRC). For instance, it can provide hourly results on the impact of higher shares of variable renewables or additional infrastructure built.

More specifically, METIS is a modular energy modelling tool covering with high granularity (geographical, time) the whole European energy system for electricity, gas and heat. Simulations adopt a MS-level spatial granularity and an hourly temporal resolution (8760 consecutive time-steps per year). Uncertainties regarding demand and RES power generation are captured thanks to weather scenarios taking the form of hourly time series of wind, irradiance and temperature, which influence demand (through a thermal gradient), as well as PV and wind generation. The historical spatial and temporal correlation between temperature, wind and irradiance are preserved.

The Commission will be the owner of the final tool and will make efforts with the Contractors to maximise transparency concerning the modelling techniques applied within, with the final goal being to offer all relevant METIS modules and data as open-source, as well as publish all produced material (from documentation to reports of studies performed with METIS).

2.2. MAIN CHARACTERISTICS OF THE POWER MARKET MODULE

Calibrated Scenarios – METIS has been calibrated to a number of scenarios based either on ENTSO-E TYNDP 2014 or PRIMES 2016 scenarios. METIS versions of PRIMES scenarios include refinements on the time resolution (hourly) and unit representation (explicit modelling of reserve supply at cluster and MS level). Data provided by the PRIMES scenarios include: demand at MS-level, primary energy costs, CO_2 costs, installed capacities at MS-level, interconnection capacities.

Geographical scope – In addition to EU Member States, METIS scenarios include ENTSO-E countries outside of EU (Switzerland, Bosnia, Serbia, Macedonia, Montenegro and Norway) to model the impact of power imports and exports on the MS.

Market models – METIS market module replicates the market participants' decision process. For each day of the studied year, the generation plan (including both energy generation and balancing reserve supply) is first optimised based on day-ahead demand and RES generation forecasts. Market coupling is modelled via NTC constraints for interconnectors. Then, the generation plan is updated during the day, taking into account updated forecasts and asset technical constraints. Finally, imbalances are drawn to simulate balancing energy procurement.

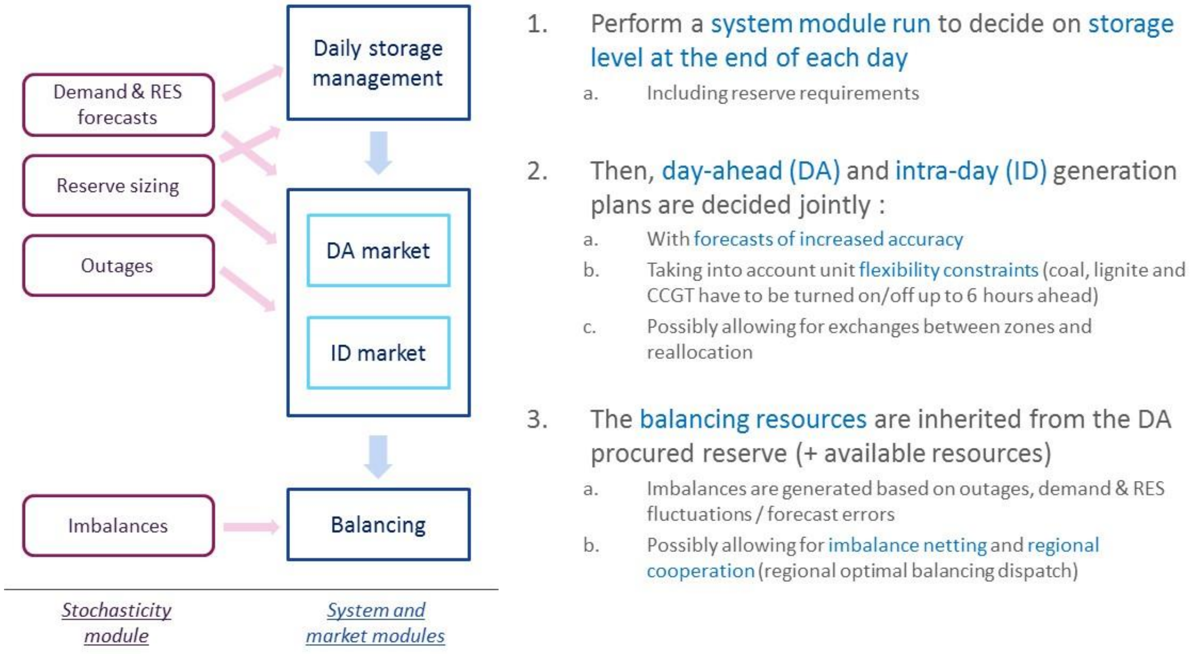


Figure 2 : Simulations follow day-ahead to real-time market decision process

Imbalances – Imbalances are the result of events that could not have been predicted before gate closure. METIS includes a stochasticity module which simulates power plant outages, demand and RES-e generation forecast errors from day-ahead to 1-hour ahead. This module uses a detailed database of historical weather forecast errors (for 10 years at hourly and sub-national granularity), provided by ECMWF, to capture the correlation between MS forecast errors and consequently to assess the possible benefits of Imbalance Netting. The stochasticity module also includes generation of random errors picked from various probability distributions either set by the user or based on historical data.

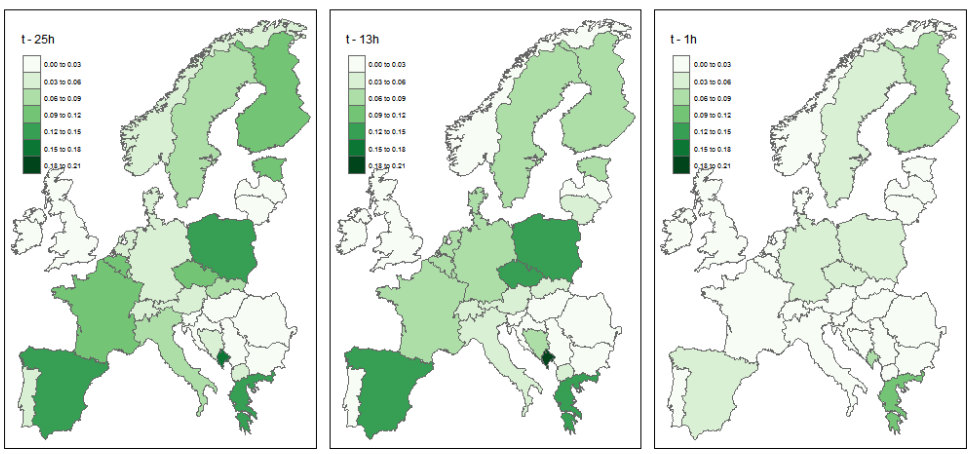


Figure 3 : Example of wind power forecast errors for a given hour of the 10 years of data.

Reserve product definition – METIS simulates FCR, aFRR and mFRR reserves. The product characteristics for each reserve (activation time, separation between upward and downward offers, list of assets able to participate…) are inputs of the model. METIS also includes a simplified representation of the use of Replacement Reserve during the intraday timeframe.

Reserve dimensioning – The amount of reserves (FCR, aFRR, mFRR) that has to be secured by TSOs can be either defined by METIS users or computed by the METIS stochasticity module to assess the level of reserves that is required to ensure enough balancing resources are available under a given probability. Hence, METIS stochasticity module can take into account the statistical cancellation of imbalances between MS and the potential benefits of regional cooperation for reserve dimensioning.

Balancing reserve procurement – Different market design options can be also compared by the geographical area in which TSOs may procure the balancing reserves they need. In case of regional cooperation for reserve procurement, interconnection capacity has to be reserved for mutual assistance between MS, so that each MS can face similar security of supply risks. Moreover, METIS users can choose whether demand response and renewable energy systems are allowed to provide balancing services.

Balancing energy procurement – The procurement of balancing energy is optimised following the same principles as described previously. In particular, METIS can be configured to ban given types of assets, to select balancing energy products at national level, to share unused balancing products with other MS, or to optimise balancing merit order at a regional level.

3. DAY-AHEAD AND INTRADAY MARKETS

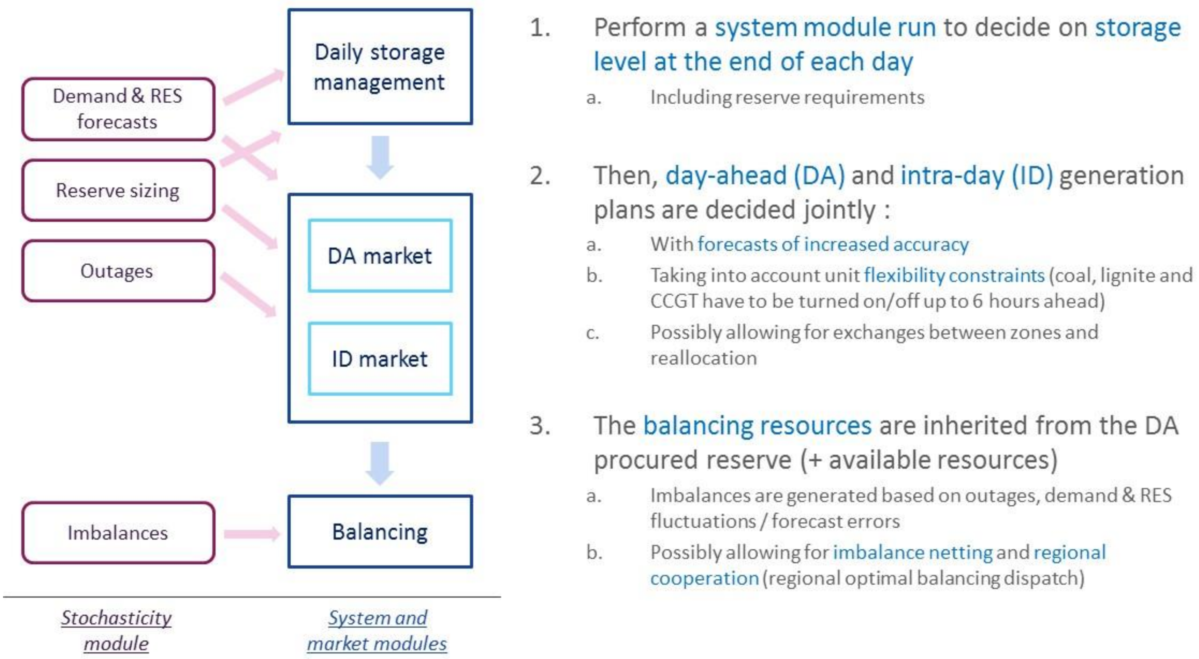
This section presents the main METIS features when it comes to the simulation of day-ahead and intraday markets.

3.1. GENERAL SIMULATION PROCESS

METIS simulates the successive clearing of short-term power markets, including day-ahead, reserve procurement and intraday markets, using fundamental data on the power systems (installed capacities, fuel costs) and market design rules such as priority dispatch, banning or granularity of markets. The balancing market simulation is described in Section 0. For intraday market simulation, METIS has a strong focus on the effect of weather forecasts on the outcomes of these power markets: producers' revenues, market prices, net positions and flows.
An hourly time resolution is used in the simulations, which are generally run over a year. Several realizations in terms of demand and RES profiles can be simulated, in order to estimate the distribution of producers' revenues.

3.1.1. *MODELLING OF MARKET HORIZONS*

In order to model day-ahead and intraday markets, which have different timeframes and are somehow intertwined together timewise, additional market-specific variables are added, compared to the METIS system module. For each physical asset (production, storage or transmission), the production is thus split into the sold/bought market volumes on the day-ahead and intra-day markets. Similarly, demands are split into sold/bought market volumes on the different market horizons. Hence, day-ahead decisions are not firm and can be readjusted in intraday, according to new RES generation and demand forecasts.



Over the year, 8760 simulations are performed, hour by hour. For each simulation, the optimization horizon is 48h. Market clearing constraints ensure that market decisions are taken as soon as the considered market closes, with respect to the supply-demand equilibrium. Thus, day-ahead sales are fixed every day at midday for the day to come, starting at midnight. In the same way, intra-day sales are set every hour for the next hour.

NOTATION:

- Index i refers to a particular generation asset
- $P_i(t)$: Generation variable of cluster i at time step t

- $v_i^{DA}(t)$: Volume sold on the day-ahead market by cluster i at time step t
- $v_i^{ID}(t)$: Volume sold (can be negative) on the intra-day market by cluster i at time step t
- $D(t)$: Demand at time step t
- $d^{DA}(t)$, $d^{ID}(t)$: Demand on the day-ahead market and adjustment on intraday (can be negative)

CONSTRAINTS:

Consistency between market horizons:

$$P_i(t) = v_i^{DA}(t) + v_i^{ID}(t)$$
$$D(t) = d^{DA}(t) + d^{ID}(t)$$

Market clearing constraints:

Equilibrium between demand and supply for each market:

$$\sum_{i \in \{assets\}} v_i^{XX}(t) = d^{XX}(t), \text{ for } XX \in \{DA, ID\}$$

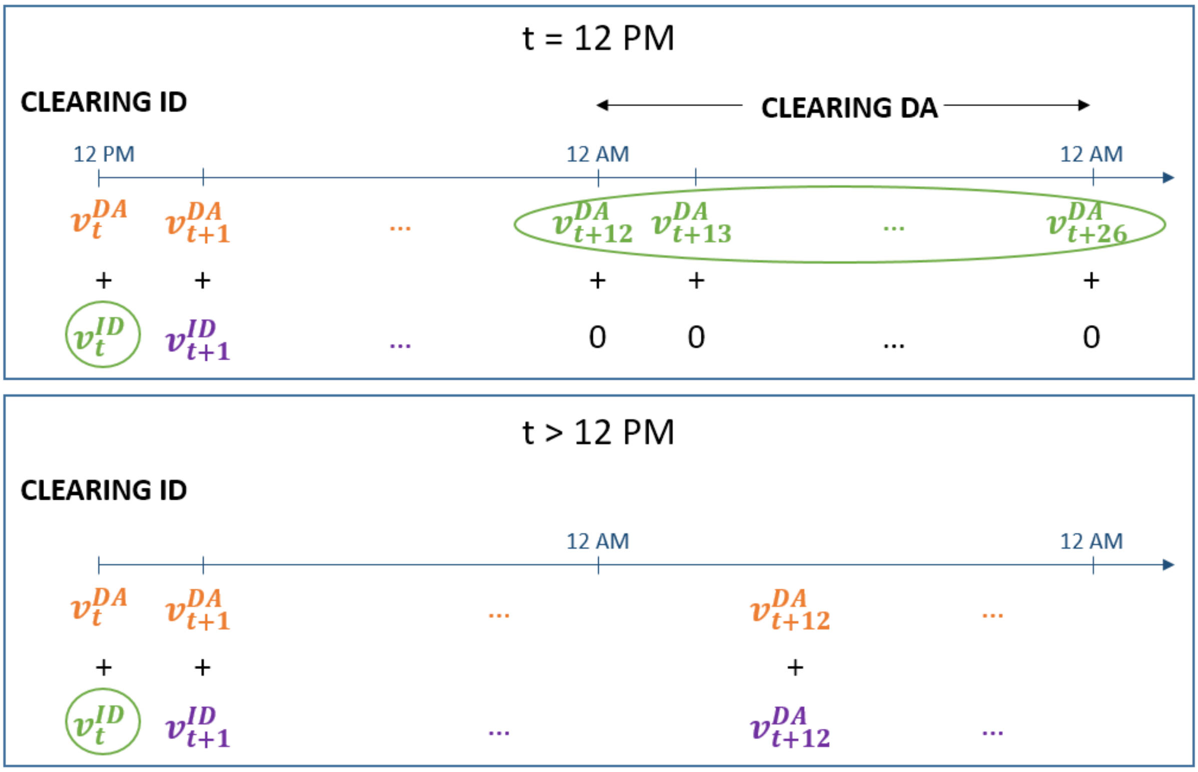
For the sake of notation simplicity, imports, exports, spillage and loss of load are included in {assets}.

NB: The dual variables (outputs of METIS embedded solver) associated with the above constraints represent the marginal cost of the market XX at the time step t.

Moreover, we assume that each production asset offers all it can (according to its forecast) to the furthest-looking market available, that is day-ahead, then intraday. This adds the following constraints:
From midnight the next day until the end of the optimization horizon, only day-ahead is available:

- $v_i^{ID}(t) = 0$, with $t \in [12AM_{D+1} ; 12AM_{D+2}]$
- $d^{ID}(t) = 0$, with $t \in [12AM_{D+1} ; 12AM_{D+2}]$

In other words, intra-day variables are enforced to be zero while the day-ahead market is still open. The graphs below summarize the market clearing constraints for t = 12 PM or for any other t. For a simulation at the time step t, the fixed variables are in orange, the free variables are in purple and the free variables that are retained as inputs for next simulations are in green.



Additional market constraints can be added if needed

Banning rules:
Some assets may be banned from participating to a given market XX. In such a case:

$$\boldsymbol{v}_i^{\mathrm{XX}}(t) = 0$$

Interconnector capacity allocation for balancing reserve:

As described in *Technical Note T6 and T3*, a share of interconnection capacity can be allocated for regional reserve sharing. In such cases, the allocated capacity cannot be changed during intraday:

$$\boldsymbol{v}_i^{\mathrm{ID}}(t) \leq NTC - \boldsymbol{v}_i^{\mathrm{DA,reserved}}(t)$$

Other examples of use are given in the section on market distortion.

3.1.2. *Modelling of system constraints*

In addition to modelling constraints between market timeframes, METIS power market module ensures that the system module constraints (c.f. *Technical Note T6*) are enforced.

In addition to this, a link is made between the short-term (METIS power market module) and the mid-term (METIS system module) to ensure consistency in the results. This is what generally producers would do: calibrate their mid-term decisions such as mid-term hydro levels and pass on this information to the shorter-term decision making models (intraday decisions).

Mid-term hydro storage constraints[2]
Storages units have a limited energy volume that can be injected in the network in a given time range. In the case of hydraulic dams, this limit is typically annual and given by the total water inflow over the year. It usually prevents storage plants from constantly

[2] More information on hydro modelling is provided in Annex **Error! Reference source not found.**

generating power at full capacity. As a consequence, the water stored in dams has to be saved when it is not most needed to produce electricity during more demanding periods.

Such an economic-based management, applied to hydro dams at different time scales – from weekly to inter-seasonal, has to be enforced in METIS. It is done in the system module by setting a "guide" curve[3] which defines, on a weekly basis, the minimal allowed storage level. The storage level yearly time series resulting from METIS system module therefore takes into account both long-term water management (by satisfying the weekly "guide" curve) and mid-term management (through the hourly optimization).

This system-module storage level time series is then given as an input to METIS power market module which derives from it the long/mid-term water management information that must constrain short-term decisions. To do so, the storage level at the end of each optimization horizon (i.e. 48 hours) in METIS power market module must be greater than the storage level resulting from METIS system module at the same time step.

For i in {storage assets}, the constraint for the simulation at the hour h is[4]:

$$\boldsymbol{S_i^{systemModule}(h+48)} \le S_i(h+48)$$

Where $\boldsymbol{S_i^{systemModule}(h+48)}$ is the storage level at time step $h+48$ that comes out of the system module run. It is therefore a fixed bound in the power market run, where $S_i(h+48)$ is the storage level variable at time step $h+48$

Start-up delays for thermal assets

METIS market module also takes into account the fact that starting a hard coal power plant must be notified 6 hours in advance whereas only 2 hours are needed for a CCGT plant (cf. Section **Error! Reference source not found.** for more details on the unit technical parameters). At each simulation hour h, the running capacity $\bar{P}_{coal}(h+6)$ is an output of the optimization problem that will be retained as input for the following simulations. In the same way, $\bar{P}_{CCGT}(h+2)$ is also fixed at the outcome of the simulation at h.

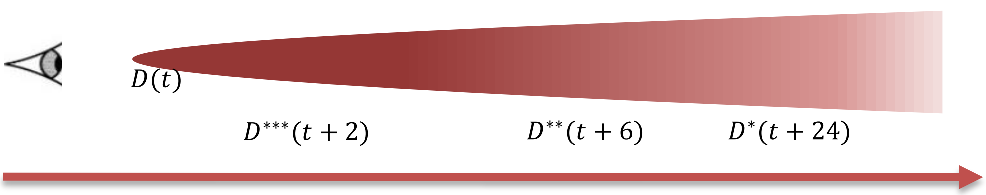
$$\bar{P}_{coal}(t) = \boldsymbol{\bar{P}_{coal}(t)}\,,\ t \in [h, h+5]$$

$$\bar{P}_{CCGT}(t) = \boldsymbol{\bar{P}_{CCGT}(t)}\,,\ t \in [h, h+1]$$

Blue variables are outputs of a previous optimization.

3.1.3. *INCLUSION OF FORECAST ERRORS*

The METIS power market module replicates a natural decision process in terms of decisions on the market horizon and in terms of progressive acquisition of more accurate forecasts. Forecast values for demand and RES productions get more and more accurate as we get closer to real-time. Put differently, the forecast for the next hour has a higher quality than the one for the day to come.



So, at each time step, demand time series are updated using the best forecast available (see Sections 3.2 and 3.3) For instance:

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[3] This curve, based on historical data, actually takes into account non-economic considerations, such as tourism, that affect water management.

[4] A variant could be to remove the upper bound of this constraint to take into account the fact that the system risks are asymmetrical (risk of loss of load if storage level is too low vs risk of underused storage)

$$
D(s) = \begin{cases} \boldsymbol{D}(s) & , s = t \\ \boldsymbol{D}^{***}(\boldsymbol{s}) & , s \in [t+1, t+2] \\ \boldsymbol{D}^{**}(\boldsymbol{s}) & , s \in [t+3, t+6] \\ \boldsymbol{D}^{*}(s) & , s > t+6 \end{cases}
$$

Consequently, day-ahead decisions are taken using a day-ahead forecast for the demand. Start-up decisions for coal and CCGT clusters are respectively taken using the h-6 and h-2 forecasts.

3.2. RES FORECAST ERROR GENERATION

The METIS market module is able to assess the interplay between RES forecast errors evolution and short-term markets (day-ahead and intraday). Since METIS in particular focuses on regional cooperation, the RES generation forecast errors conserve the observed spatial and temporal correlations.

METIS stochasticity module uses historical data of weather forecast (one value by hour, zone and horizon) to generate demand and RES forecast. However, METIS market module also includes features to generate stochastic events for a given day, in order to study a particular situation under various forecast errors and imbalances.

These data are then used for imbalances generation, reserve sizing and market simulations.

3.2.1. *METHODOLOGY*

RES generation data are computed using a power conversion model which estimates wind power and PV generation with an hourly time step, based on meteorological inputs (wind speed and solar irradiation). This model has been developed by IAEW and has been calibrated so that the capacity factors match data provided by PRIMES for 2030 (see Appendix 2 of *METIS Technical Note T6* for further details).

When it comes to the simulation of RES production forecasts, one basically uses the same power conversion model with meteorological forecasts as inputs. To that purpose, we use historical Numerical Weather Predictions (NWP)[5] provided by the European Center for Medium-range Weather Forecasts (ECMWF). As a final step to the simulation of the forecasting process, RES forecasts are statistically recalibrated using (simulations of) production realizations so as to ensure forecasts to be unbiased and with state-of-the art performance.

To simulate intra-day operations, hourly update of forecasts is derived from the most up-to-date NWP and current (i.e. present) production estimate. In between NWP updates, such a procedure must ensure improved RES forecasts performance in the first forecast hours.

[5] Numerical Weather Predictions uses state-of-the-art mathematical models of the atmosphere and oceans to predict the weather based on previous weather conditions. Hindcasts provided by ECMWF are based on a unique model and used historical weather to compute historical predictions. Therefore, the forecast performances are constant for the 10 years of weather predictions.

RES forecast errors are finally generated by computing the difference between RES production realizations and forecasts simulations.

3.2.2. ***METEOROLOGICAL DATA USED***

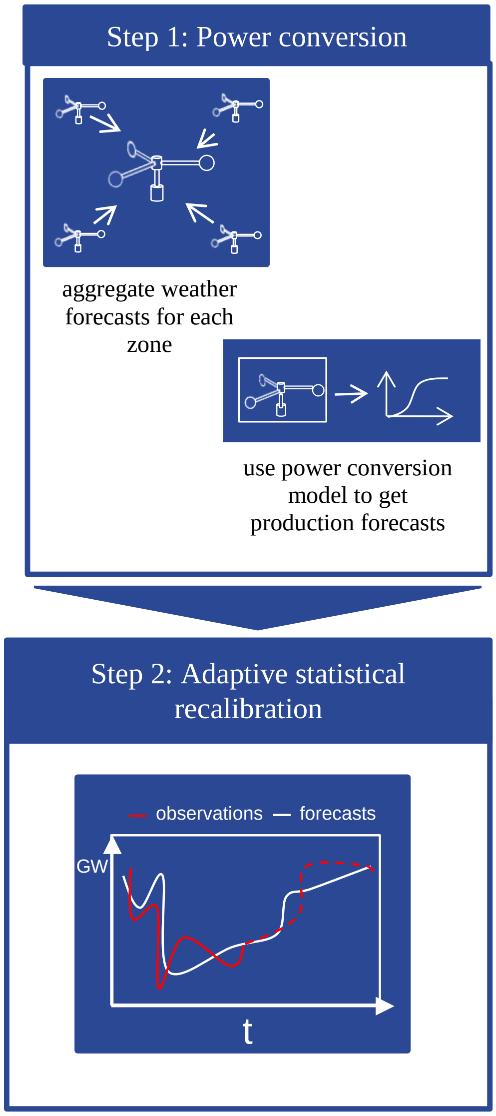
3.2.2.1. *Simulation of production realizations*

RES production realizations have been simulated at hourly granularity from the interpolation of ERA-Interim reanalysis data[6] over the period 2001-2010.

For further details on the related simulation methodology, data used and simulation results, we refer to *METIS Technical Note T6*. Yearly full load hours for both PV and onshore wind production simulations for the considered countries are also given in the document. Those simulations are now identified as real production measurements.

3.2.2.2. *Simulation of production forecasts*

We use ECMWF forecasts that have been derived from the High RESolution[7] (HRES) global model at the same spatial resolution than the ERA-Interim data (0.75° in longitude and latitude). Those forecasts cover a 20 year-long period between 1994 and 2014, but only the 2001-2010 period associated to production realizations is kept so as to generate forecast errors. Forecasts have been derived twice a day at 00h UTC and 12h UTC for 48h ahead. Initially available at a 3h temporal resolution for the first 24h ahead and at a 6h temporal resolution for the next 24h, they have been interpolated using cubic splines before spatial aggregation and power conversion.



3.2.3. ***RES FORECASTS RECALIBRATION***

To get state-of-the art forecasts performance, RES production forecasts derived from NWP require statistical recalibration. RES production forecasts derived from meteorological forecasts used as input to IAEW power conversion model require additional statistical recalibration for at least three reasons:

- to incorporate actual production estimate as additional information for forecasts actualization in between NWP actualizations,
- to remove potential bias that may lie in meteorological forecasts or may be caused by improper power conversion modelling,
- to correct approximations due to interpolation of meteorological forecasts available with sparse temporal resolution (6 hours) at horizons further than 24 hours ahead.

To deal with these limitations, we consider a statistical recalibration model that re-estimate RES production forecasts from initial forecasts, using actual production estimate as additional input. The considered model can be written as:

$$Y(z,\ r_i + h) = a_{z,r_i,h}\hat{Y}\,(z, r_i, h) + b_{z,r_i,h}Y(z,\ r_i) + c_{z,r_i,h} + \varepsilon(z, r_i, h),$$

Where Y is the production simulation, $\hat{Y}$ the production forecast derived from meteorological forecasts power conversion, z the considered zone, r the hour of day

[6]http://www.ecmwf.int/en/research/climate-reanalysis/era-interim

[7] http://www.ecmwf.int/en/forecasts/documentation-and-support/medium-range-forecasts

forecasts' actualization is derived (i.e. $r = 0, \ldots, 23$ h UTC), h the forecast horizon (in hour), ε the modeling error and i the sample day.

Parameters of the model are estimated by a least-squares approach. Normalized production is constrained so as to stay bounded[8]. To bring additional flexibility to the model, parameters are adaptively estimated using a 3 months long moving time window for statistical learning, with parameters' estimation actualized every week. This must help capture long term variations associated to the forecasting process, such as climatic variations or variations in NWP models' parameterization.

The next figure shows three time series on the same graph: realizations (simulations), forecasts made at midnight before recalibration and forecasts made at midnight after recalibration. These are time series for photovoltaic generation in Germany during the first week of 2006. For all following graphs, PV and wind generation are expressed as a ratio of installed capacity.

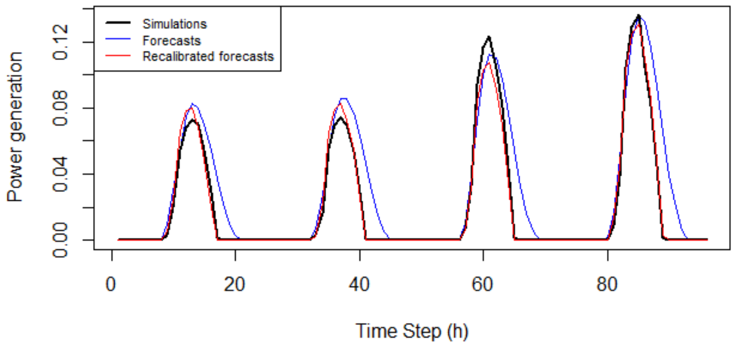


Figure 4 - Power generation given by simulations, forecasts before and after recalibration. Simulations and forecasts shown here are for the first few days of 2006 in Germany.

During the afternoon, forecasts are overestimating power generation before recalibration. It is noticeable that recalibration removes this bias.

Next figure shows the boxplot of forecast error with prediction horizon for PV generation in Germany for the midnight run.

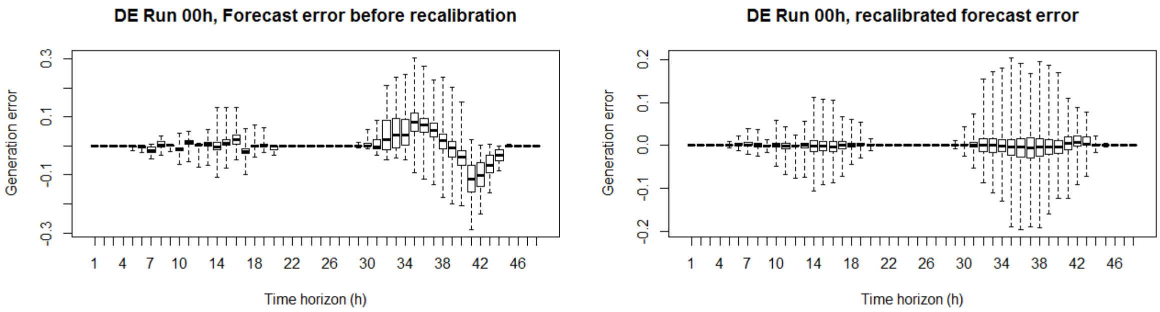


Figure 5 - Forecast error boxplot before and after recalibration.

The graph before recalibration shows that after 24 hours of time horizon, forecasts are slightly out of phase, mostly due to interpolation with a lower temporal resolution. It also shows that even for the first 24 hours of prediction, bias is not zero. Recalibration corrects both effects, as one can notice in the recalibrated forecasts boxplots. Thus, recalibration removes bias and corrects approximations due to interpolation.

3.2.4. *FORECAST MODEL PERFORMANCES*

The figure below shows the evolution of final error standard deviation for the midnight forecast run with time horizon. There is one curve for each European country.

[8] Between 0 and 1 for wind power and between 0 and a maximum production value defined for each hour of day for PV generation. Such a value is adaptively estimated using 1 month long moving time window and over the 10 years/scenarios generated from IEAW reanalysis data.

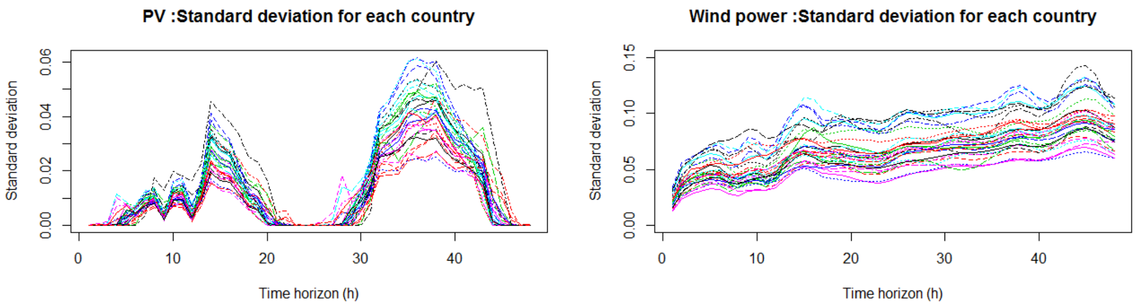


Figure 6 - Standard deviation of the final error for the midnight forecasting run for PV and Wind power.

For each country, the error standard deviation tends to increase with time horizon, as expected.

The following table gives the error standard deviation for each country, for the midnight run and a time horizon of 1, 10 and 15 hours, expressed as a percentage of installed capacity.

	PV			**Wind**		
Country	**Standard deviation (%)**			**Standard deviation (%)**		
	h = 1[9]	h = 10	h = 15	h = 1	h = 10	h = 15
AT	0	1,3	2,6	1,8	3,5	6,4
BE	0	1,4	3,2	2,0	3,9	6,4
BG	0	1,3	2,2	2,2	4,3	8,5
CH	0	1,0	2,2	1,3	2,8	5,0
CZ	0	1,2	2,4	1,7	3,5	5,6
DE	0	1,0	1,9	1,1	2,3	3,4
DK	0	1,0	2,2	2,0	3,5	5,2
EE	0	1,1	1,9	2,0	3,9	5,0
ES	0	0,9	2,1	1,2	3,0	4,0
FI	0	0,8	1,3	1,7	3,9	4,4
FR	0	1,0	2,2	1,2	2,6	4,0
GB	0	0,9	1,9	1,6	3,3	4,3
GR	0	1,3	2,0	1,8	4,6	6,6
HR	0	1,9	3,0	1,8	4,3	5,8
HU	0	1,0	2,0	1,9	3,8	6,5
IE	0	1,2	3,0	2,3	4,3	5,8
IT	0	0,8	1,8	1,2	2,7	4,6
LT	0	1,3	1,9	1,7	3,5	4,5
LU	0	1,4	3,1	1,8	3,5	5,4
LV	0	1,1	1,8	2,1	4,0	5,5
MK	0	1,5	2,6	1,5	2,8	4,9
NL	0	1,1	2,6	2,0	3,9	6,1
NO				1,4	4,4	5,5
PL	0	0,9	1,6	1,4	3,2	5,0
PT	0	1,2	2,9	1,9	4,9	7,2
RO	0	1,2	2,0	1,8	3,8	6,6
RS	0	1,1	2,1	1,7	3,1	5,8
SE	0	0,6	1,3	1,5	3,3	3,9
SI	0	1,3	2,8	1,9	3,8	5,6
SK	0	1,1	2,1	1,4	2,8	4,5

Table 1 - Standard deviation of PV and Wind power forecast errors for the midnight run at 1h, 10h and 15h time horizons.

[9] For PV midnight h-1 forecasts, the standard deviation is null as there is no PV generation during night.

Additional verification statistics were investigated to ensure forecasts were well calibrated and with satisfying performance depending on relevant parameters (hour of the day for demand and PV production, production level for wind power, etc.). One can see for instance in Figure 7 (left panel) the increased uncertainty associated to forecasts of wind power production at high production level. Another interesting aspect was to look at performance improvement due to spatial smoothing of errors (Figure 7 right panel).

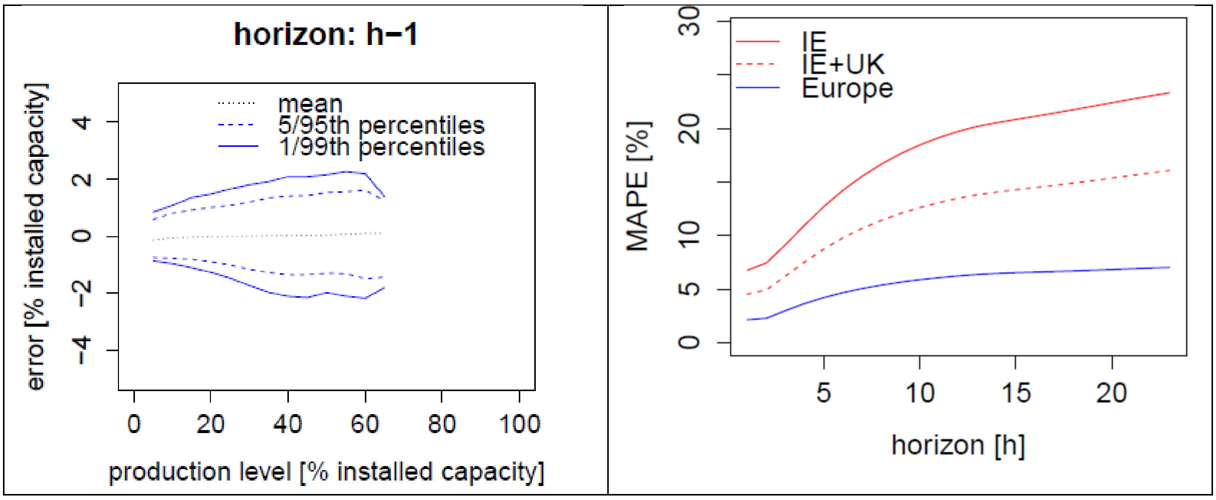


Figure 7 : Forecast errors distribution depending on production level for the aggregated European wind power production, one hour ahead (left panel). Forecasts performance improvement due to spatial smoothing of errors for wind power production. Here performances are measured using the Mean Absolute Percentage Error (MAPE) criterion.

3.3. Demand forecast error generation

METIS stochasticity module generates forecast errors for power demand at several short-term horizons (up to 24 hours). These forecast errors are then used for imbalance generation, reserve sizing and in the market simulations.

3.3.1. *Methodology*

METIS database includes 50 years of power demand hourly time series. These data have been computed using:

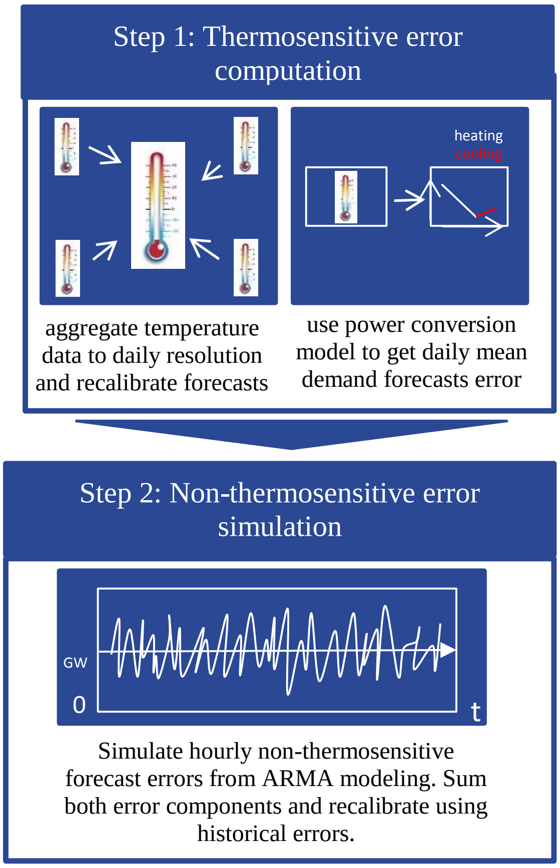
- Hourly demand time series for one year, published by ENTSO-E. These time series include evolutions of the structure of the power demand, as estimated by ENTSO-E in its V1 and V3 2030 scenarios[10].
- 50 years of daily mean temperature data.

The designed model generates hourly demand time series from daily temperature data based on:

1. a thermosensitive component which estimates the daily mean demand level from the daily mean temperature using a statistical model,
2. a non-thermosensitive component representing the hourly variability of the demand residuals (i.e. the difference between the hourly demand and the first component, the latter being constant over a day).

[10] In the absence of demand historical hourly data, ENTSO-E v1 hourly profiles are used.

For more information about this model, we refer to *METIS Technical Note T6* on Power System Module.



To generate demand forecast errors, we simulate errors in forecasting both components of the demand generation model. The error is then computed from the sum of the first and second component forecast errors.

The forecast of the first component is basically obtained by feeding the associated statistical (piecewise linear) model with daily mean of temperature forecasts provided by ECMWF.

To simulate the forecasting error of the non-thermosensitive component, we use a statistical ARMA model fitted to real forecasting error data provided by the ENTSOE[11]. Such a model allows to capture the temporal correlation but neglect the spatial correlation in the non-thermosensitive part of forecast errors from different countries.

3.3.2. *DATA USED FOR THE SIMULATION*

3.3.2.1. *Thermosensitive component of demand forecasts*

As for the RES forecast errors generation, we use ECMWF temperature forecasts[12] to produce forecasts of the demand's thermosensitive component.

3.3.2.2. *Non thermosensitive error component*

We use historical day-ahead forecasting error data provided by the ENTSOE. For the calibration of the dedicated ARMA model, we used data from a country whose electrical demand has low sensitivity to temperature.

3.3.3. *MODEL CALIBRATION*

3.3.3.1. *Recalibration of temperature forecasts*

We either observed a somewhat constant temperature forecasts bias, or a bias with annual seasonality. Thus, we used a linear model to recalibrate temperature forecasts with parameters estimated on a monthly basis.

3.3.3.2. *Calibration of the ARMA model on the non-thermosensitive error component*

Historical day-ahead forecast errors are sometimes biased[13]. To be consistent with the rest of the methodology, we centered the error time series by computing its difference with the daily mean error at hourly granularity.

To choose an appropriate ARMA model to fit to the data, we looked at the autocorrelation (ACF) and partial autocorrelation (PACF) functions. The former has a shape that tapers to

[11] https://transparency.entsoe.eu/

[12] http://www.ecmwf.int/en/forecasts/documentation-and-support/medium-range-forecasts

[13] This may come from the use of an asymmetric cost function undertaken by the related operational forecasting system.

0 while the second shows non-null values at specific time lags, which indicates[14] an auto-regressive AR process. Focusing on the non-null coefficients of the PACF function, while trying to keep the model's order reasonable, we chose an AR(24) model. The coefficients of the fitted model are given in the following table:

Table 2 : AR(24) coefficients estimation from maximum likelihood fit to the centred day-ahead demand forecast error time series of the Dutch national electric demand.

Lag (h)	1	2	3	4	5	6	7	8	9	10	11	12
Coef	.55	.12	-.03	-.06	-.04	-.06	-.03	-.03	-.03	-.04	-.05	-.02

Lag (h)	13	14	15	16	17	18	19	20	21	22	23	24
Coef	-.01	-.06	-.03	.00	.00	-.02	-.01	-.03	.00	.02	.04	.04

3.3.4. *MODEL PERFORMANCES*

Demand forecasts update has been simulated through scaling of day-ahead forecast errors. Scaling factors have been determined by linear interpolation of MAPE (Mean Absolute Percentage Error) performances observed for different prediction horizons. We used both performance results observed in ENTSOE historical error data (for h = 24) and in the literature[15] (for h = 1), to compute these factors. A summary of the model performances that can be observed across prediction horizons is given in the table below.

[14] https://onlinecourses.science.psu.edu/stat510/node/64

[15] "A comparison of univariate methods for forecasting electricity demand up to a day-head", Taylor et al., International Journal of Forecasting, 2006, vol. 22(1): p.1-16.

Country	Standard deviation (%)		
	h = 1	h = 13	h = 23
AT	0,4	2,4	4,1
BE	0,4	1,1	1,6
BG	0,4	1,4	2,2
CH	0,3	1,1	1,8
CZ	0,1	0,9	1,5
DE	0,4	1,7	2,7
DK	0,4	0,5	0,6
EE	0,4	1,2	1,8
ES	0,4	0,7	0,9
FI	0,3	1,1	1,8
FR	0,3	0,8	1,1
GB	0,3	1,1	1,7
GR	0,3	1,1	1,8
HR	0,4	0,9	1,3
HU	0,2	0,9	1,5
IE	0,3	1,1	1,7
IT	0,4	0,9	1,3
LT	0,3	1,0	1,7
LU	0,4	1,7	2,8
LV	0,3	1,0	1,6
MK	0,4	1,4	2,3
NL	0,4	1,2	1,8
NO	0,3	1,0	1,6
PL	0,4	0,9	1,4
PT	0,4	1,1	1,7
RO	0,4	0,8	1,1
RS	0,4	1,0	1,5
SE	0,3	1,0	1,6
SI	0,4	2,1	3,5
SK	0,5	1,3	2,0

Table 3 : Standard deviation of demand forecast errors for prediction horizons h=1, h=13 and h=23

3.4. Outages

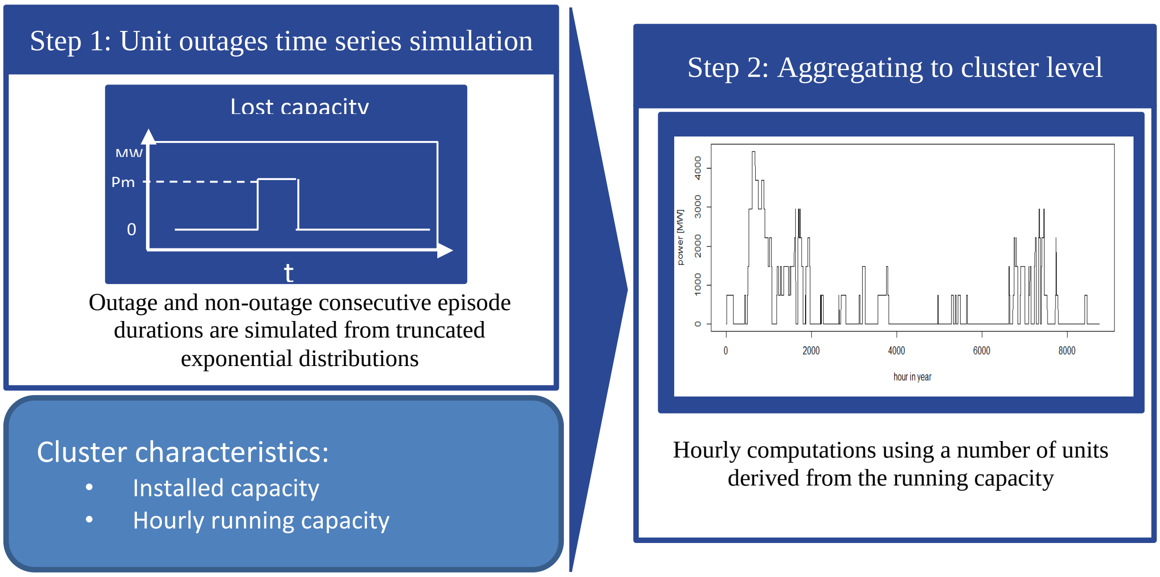
3.4.1. *Methodology*

The availability of production clusters incorporates stochastic simulation of unplanned outages. This is in particular used for the generation of imbalances and thus for reserve sizing.

For each cluster unit, a time series describing the unit's availability (or non-availability) is generated from the concatenation of consecutive episodes with random durations sampled from truncated exponential distributions[16].

For each cluster, hourly lost capacity due to units' outages is computed from the sum of units' availability, considering a number of units derived from the cluster's hourly running capacity.

[16] Exponential distribution is a usual hypothesis found in the literature to model unit outage duration distribution, see for instance «System availability with non-exponentially distributed outages", Cao et al., IEEE Transactions on Reliability, 2002, vol. 51(2), p.193-198. doi: 10.1109/TR.2002.1011525.



3.4.2. *DATA USED FOR SIMULATIONS*

Annual mean outage durations were based on a literature survey. Using the annual mean number of outages computed from historical data provided by RTE (Réseau de Transport d'Electricité), we derived the mean duration of a single outage. Minimum and maximum outage durations were also derived from RTE historical data. All these parameters used for simulation are given in the table below.

Type de cluster	Mean annual outage duration (h)	Mean outage duration (h)	Minimum outage duration (h)	Maximum outage duration (h)
Coal fleet	490	233.38	0	6517
Lignite fleet	190	233.38	0	6517
Oil fleet	290	61.28	0.3	3022
OCGT	330	151.17	0.2667	8088
CCGT	330	151.17	0.2667	8088
Nuclear fleet	50	64.59	0	2931.5

Table 4 : Annual outage duration along with parameters of the duration distribution for one outage are given for each considered technology.

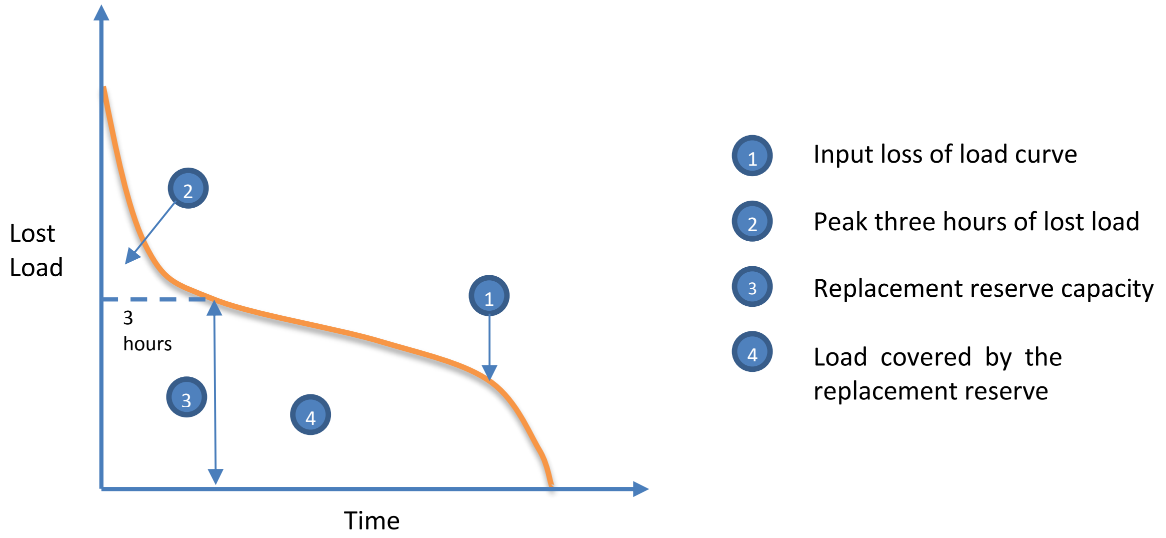
3.5. LOSS OF LOAD AND REPLACEMENT RESERVE

Unplanned events such as a reduction of wind or PV generation, an increase of demand or a producing power plant outage, might lead to loss of load in the model, when the available capacities are not sufficient to face the mismatch between supply and demand. In real markets, Replacement Reserve (capacity which can start in a few hours) is procured at day-ahead (or before) and allows to avoid such loss of load. As Replacement Reserve is not modelled in METIS, periods with consecutive hours of loss of load can happen.

In order to compare fairly the different policy options, a proxy has been developed to count loss of load. Instead of counting the loss of load at a price of 15k€/MWh, the cost of a corresponding replacement reserve is computed ex-post for each country. This cost is computed as:

- Investment cost of peak units (60 k€/MW/yr) to cover most of the loss of load (all but 3 hours)
- Production cost of peak units at 180€/MWh (variable cost of oil fleets, including CO_2 emissions) to cover most of the loss of load (all but three hours)
- VoLL (15k€/MWh) for the remaining three hours of loss of load.

The computation process is described below.



3.6. BIDDING BEHAVIOUR

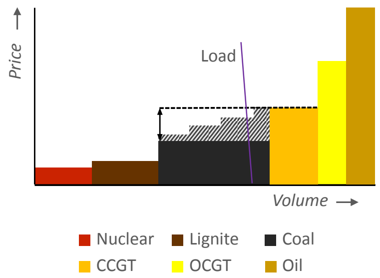
METIS is able to simulate the impact of several bidding behaviours, including scarcity pricing, on market players revenues and on marginal costs.

Marginal Cost Bidding

- Technology bids according to actual production costs
- No kind of mark-up
- Energy only market with perfect competition

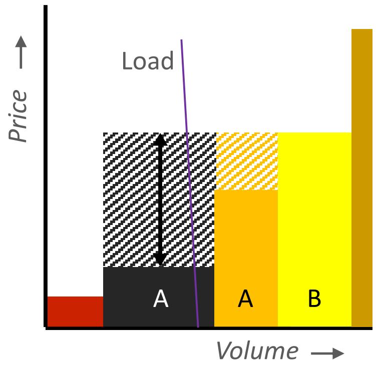
Competitive Bidding

- Mark-up depending on utilization of cluster's capacity
- Stepwise mark-up with growing utilization
- Overall bid never exceeds marginal costs of next technology cluster
- NB: Scarcity pricing is a particular case of competitive bidding. It occurs when the most expensive technology is being used.



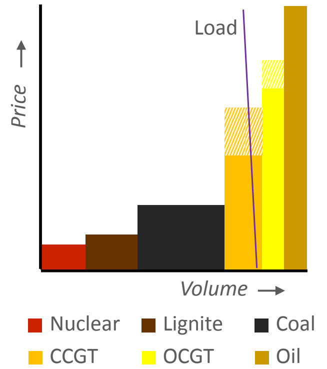
Oligopoly Bidding

- Technology with highest costs needed for load coverage adds mark-up
- Mark-up based on market share and portfolio
- Increase to production costs of next technology with different operator



Fixed Costs Bidding

- Each bid includes fixed costs (OPEX and/or CAPEX)
- Mark-up depends on type and age of technology
- Mark-up is limited to next technology cluster’s bid



Most of the parameters used to simulate the effect of bidding behaviours come from the system module (in the case of mark-ups depending on how far the next generation in the merit order is, for instance).

Yet, METIS needs the user to input some additional parameters, like:

- The level of price caps
- In the case of oligopoly bidding, the ownership distribution of each cluster among operators.

NB: The model simulates the effect of bidding behaviours on prices, focusing on the marginal unit, which is the one that ultimately fixes the price. Currently, the model does not consider the possible impact on volumes and flows.

4. Balancing markets

4.1. Inputs

The balancing market simulation is computed ex-post on a given year of weather data. Hence, it takes as input for each hour of the year:

- The set of units which procured reserve, as a result of the system simulation (cf section 3.1).
- For each unit, input parameters (pmax, pmin, cluster characteristics) and output results from the day-ahead model and reserve procurement (maximum downward/upward variation).
- For each unit, variable costs (fuel costs or "water value" for hydro storage).

Technology	Variable cost
Hydro	Day-ahead water value (dual value associated to the storage constraint)
Industrial demand response	225€/MWh
Other demand response	Day-ahead price
Other fleets	Day-ahead production cost

- Planned power exchanges for NTCs.
- Balancing market configuration. Balancing services can be procured either on a national basis or with regional cooperation (including imbalance netting). Additional interconnection capacity, or on the contrary penalty to use interconnectors, can be added for balancing exchanges.

The activation cost of balancing energy is assumed to have two components: a fixed activation cost plus the variable cost. The same is valid for downwards reserves: fixed activation minus variable cost (saved fuel costs or water value). The fixed activation cost has been estimated by comparing historical balancing costs to the costs of electricity. This analysis suggests producers add a mark-up of around 8€/MWh to their variable cost. Competitive pressure would likely drive this mark-up down. This effect has not been modelled.

4.2. Outputs

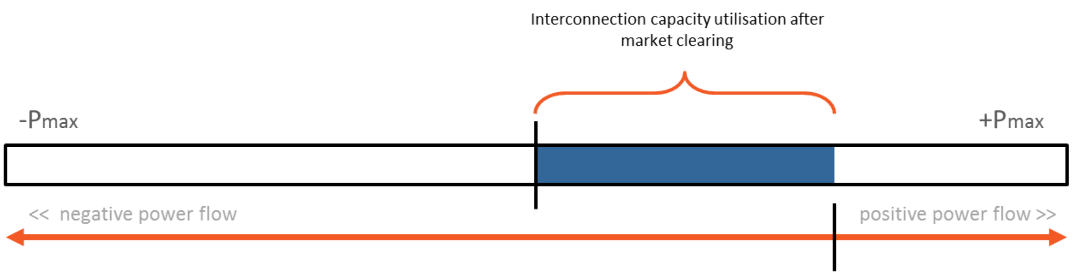
METIS balancing market module computes:

- Imbalances for each country, with a 5 minute granularity, aFRR and mFRR calls on a national basis[17]
- Optimal dispatch of aFRR and mFRR balancing products, using a national or regional merit order. The merit order is deducted from total activation or deactivation costs, which is composed of a participation cost (constant for all fleets) and a variable cost (dependent of the technology):
    - Activation cost for upward reserve: Participation cost + Variable cost
    - Deactivation cost for downward reserve: Participation cost – Variable cost

[17] Further details are available in *METIS Technical Note T6*

Therefore, expensive fleets are called first for downward reserve, while cheap fleets are called first for upward reserve. However, imbalance netting (which consist in the cancellation of opposite reserve demand) is prioritized if sufficient interconnection capacity is available.

Under regional cooperation, balancing exchanges are constrained by interconnection capacity. For a given type of balancing product (aFRR or mFRR), balancing activations with opposite direction are cancelled, if the interconnection capacity allows to do it.



- Statistics are gathered on balancing costs, interconnection use and number of time steps for which balancing activation exceeds reserve size.

The impact of balancing market on the following intraday gateway is not modelled.