

# **Models description**

Plan4res is an electricity system optimisation and simulation tool, composed of the 3 following models :

- A Capacity expansion model (CEM) aimed at adapting the electricity mix,
- A seasonal storage valuation model (SSV) aimed at optimizing the management of seasonal storages
- A Simulation model (SIM), aimed at optimizing the short term operation of the system. The simulation is ran on every scenario one after the other and it executes a Unit Commitment model (UC) sequencially on the whole time period.

#### Those 3 models cannot be described independently as:

- The Capacity Expansion Model uses the Seasonal Storage Valuation Model for the evaluation of its operation cost function
- The Seasonal Storage Valuation Model itself uses the Unit Commitment Model for solving its inner transition problem.

This means that CEM cannot be ran without SSV and UC, and SSV cannot be ran without UC, while UC can be ran alone, and SSV-UC can be ran without CEM. SIM cannot be ran without UC.

All models share the exact same set of data.

### 1 Capacity Expansion Model

The capacity expansion model is concerned with finding a (better) or ideally optimal set of assets including generation plants, interconnection capacities between clusters and distribution grid capacities, for the considered time horizon. Here optimal means, providing the least-cost set of assets, while accounting at best for the modelled constraints.

The objective is thus to design the optimal generation mix with the optimal transmission and distribution grid capacities for a given long-term horizon (e.g. 2050). The problem then consists in minimizing the sum of two terms:

$$\min_{\kappa} \left\{ C^{capex}(\kappa) + \max_{\eta \in U} C^{opex}(\kappa, \eta) \right\} \quad (5)$$

Where:

- (a)  $\kappa$  denotes a vector containing the investment capacities either on generation technologies at each node of the network or on some lines of the transmission or distribution grid;
- (b) U is the distinct and finite set of "meta-scenarios" (e.g., some choice of climate-change trajectory);
- (c)  $C^{capex}(\kappa)$  denotes the annualized investment cost induced by installing the ca-pacity  $\kappa$  in the electrical system;
- (d)  $C^{opex}(\kappa,\eta)$  denotes the expected operation cost of the system with the given installed capacity  $\kappa$  on the typical time horizon (for instance the typical year 2050), under the assumption of the metascenario  $\eta$ .

Additionnal constraints can be included:

1. Each region is able to produce the amount of energy required to meet the demand

For each Region z:

$$\sum_{t,i \in \mathbb{Z}} \kappa_i P_{i,t}^{max} \sum_{1 \le j \le 37} \alpha_{i,t,j} \ge \sum_{t,j} D_{t,j}^{\mathbb{Z}}$$

$$\sum_{t,i \in \mathbb{Z}} \kappa_i P_{i,t,j}^{max} \ge \sum_{t,i} D_{t,j}^{\mathbb{Z}}$$

 $D_{t,i}^{Z}$ : Demand of region Z, at time t for scenario j

 $\alpha_{i,t,j}$ : RES load factor of technology i at time t for scenario j, with  $0 \le \alpha_{i,t,j} \le 1$ 

 $P_{i,t,i}^{max}$ : maximum power of technology i, at time t, scenario j

 $\kappa_i$ : number of units of techno i in region z

2. Each region has to reach a target in terms of RES share (including hydro)

$$\begin{split} \sum_{t,i \in ENR \cap Z,j} \kappa_i P_{i,t}^{max} \alpha_{i,t,j} &\geq \rho \sum_{t,i \in Z,j} \kappa_i P_{i,t}^{max} \alpha_{i,t,j} \\ \sum_{t,i \in ENR \cap Z,j} \kappa_i P_{i,t,j}^{max} &\geq \rho^Z \sum_{t,i \in Z,j} \kappa_i P_{i,t,j}^{max} \end{split}$$

 $\rho^Z$  : share of Renewable energy for zone Z with  $~0 \leq \rho^Z \leq 1$ 

The 2 constraints are not to be used together.

## 2 Seasonal Storage Model

The Seasonal Storage Model solves a mid-term problem, where mid-terms stands usually for annual. This problem consists in evaluating an approximation of the expected operation cost,  $C^{opex}(\kappa, \eta)$ , for a given vector of installed capacity,  $\kappa$ , under the assumption of the meta-scenario  $\eta$ .

The mid-term horizon is a set of stages  $S = \{s_0, s_1, \dots s_n\}$  (eg. weeks), subdividing the typical period (eg 1 year) on which operation costs are evaluated. Each stage is divided in time steps  $\{t_0, t_1, \dots t_n\}$  (eg. Hours).

Note that uncertainties (such as reservoir inflows, demand, outages or intermittent generation) are impacting operation decisions which are made dynamically along the mid-term horizon, while those uncertainties are progressively revealed and the forecasts are accordingly updated. Hence, the SSV model consists of a multi-stage stochastic optimization problem, aiming at minimizing the sum of operation costs on each stage s:

$$C^{opex}(\kappa) = \min_{x \in X} E \left[ \sum_{s \in S} C_s^{opex}(x_s) \right]$$

Where:

•  $x = (x_s)_{s \in S}$  is the sequence of operation decisions taken at the beginning of each stage. These decisions are supposed to be non-anticipative, in the sense that decisions  $x_s$  made at stage s should only depend on the past realizations of uncertainties.

X is the feasible set associated with operation decisions. In particular, it includes the already invoked non-anticipativity constraint relating decisions to observed uncertainties. We also emphasize the presence of dynamical constraints (relating reservoir levels between two stages, ramping rates or any other conditions that involves linking adjacent time steps). This prevents us from taking decisions independently between two stages.

•  $C_s^{opex}$  represents the operational cost on the stage s as a function of decisions  $x_s$ . Notice that  $C_s^{opex}$  depends implicitly on the installed capacity  $\kappa$  and on uncertainties revealed at stage s (demand, inflows, intermittent generation) so that the expectation appearing in (6) is related to the probability distribution of those implicit uncertainties. Furthermore, the expectation is not to be taken over the set of meta-scenarios U, since these are assumed to be given without a (probability) distribution: they represent plausible futures against which we want to hedge, but which cannot be reasonably equipped with a distribution.

This problem is solved by time decomposition using stochastic dynamic programming. At each stage s, a transition problem is solved, involving operational cost of stage s  $C_s^{opex}$  and the cost-to go function giving the minimum future operational expected cost. The transition cost is evaluated by the EUC Model (see below).

### 3 Unit Commitment Model (UC)

The unit commitment problem (UC) solves the short-term horizon problem (short-term meaning usually daily or weekly), where operational decisions are provided at one stage  $s \in S$ , in a deterministic setting, taking into account the "value" that seasonal storage units can bring to the system via the cost-to-go function. The UC occurs in two ways.

- (a) The UC optimization mode solves the transition problem of SSV with a convexification of the operational constraints. In fact, it is intended to provide cutting plane approximations of cost-2-go functions. Notice that the associated operational decisions may be infeasible since non-convex technical constraints have been convexified. The advantage is that the UC optimization mode should run reasonably fast.
- (b) The UC simulation mode solves the transition problem, without any convexification of technical constraints. This mode is intended to provide a feasible generation dispatch, on a given sub-period. It uses the cutting plane approximations of the cost-2-go functions provided by SSV and is based on a feasible recovery heuristic ensuring the feasibility of operation decisions. The computing time required to run the EUC simulation mode could be significantly greater than that to run the UC optimization mode.

However, in simulation mode, both investment capacities  $\kappa$  and approximations of the cost-to-go functions remain fixed. Therefore in total, likely, the simulation model will be faster than the optimization mode.

To compute the expected cost,  $C^{opex}(\kappa)$  post-optimization, it is more relevant to rely on feasible decisions and consequently to use the EUC simulation mode implemented sequentially for each stage  $s \in S$  and averaged over Monte Carlo simulations of the random vector  $\xi$ . In this fashion we can compute a stochastic upper bound on the actual optimal cost of operation for the current investment capacity  $\kappa$ .

Various kinds of flexibilities involving both generation, storage and consumption are dealt with:

- Dynamic operation constraints of power plants (ramping constraints, minimum shut-down duration, ...)
- Dynamic operation of storage (including battery-like storages and complex hydro-valleys modelling)
- Demand-Response (including eg. household dynamic consumption load-shifting or load curtailment)

The UC can also account for both transmission and distribution networks:

- Transmission Network representation: from a copper plate approach to a 'clustered' approach with limited transport capacities.
- Electricity distribution limited capacities and reinforcement costs