Models description

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Plan4res is an electricity system optimization 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. It computes the Bellman values (= cost-to-go functions) that represent the future expected economic value of the seasonal storages' levels at time stages. This is necessary to know when to best use a "free" but limited and uncertain resource such as water inflows to large hydropower reservoirs: should the hydropower plant produce now and discharge part of its stored water, for example to avoid starting up a costly coal plant to meet demand, or should water be kept for a latter use, for example because present demand is low and RES generation is sufficient?
- A Simulation Model (SIM), aimed at optimizing the short-term operation of the system. The simulation is run on every scenario one after the other using a Unit Commitment model (UC) sequentially on the whole time period. The cost-to-go functions computed by the SSV are used as a variable cost for the generation of seasonal storages.

Those 3 models cannot be described independently as:

- The CEM uses the SSV model for the evaluation of its operation cost function which include the economic values and opportunities offered by seasonal storages.
- The SSV model itself uses the Unit Commitment model for solving its inner transition problem. Indeed, to assess the value of storages on the long run, the model sequentially computes future cost-to-go functions that represent how much a given amount of energy storage can reduce future operation costs (for example by using hydropower to save on expansive fuel costs). To do so, a lot of Unit Commitment problems are solved in a backward recursion using an algorithm called dynamic programming.

This means that CEM cannot run without SSV and UC, and SSV cannot run without UC, while UC can run alone provided the right inputs, and SSV-UC can run without CEM. SIM cannot run 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 and interconnection capacities between clusters 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 capacities for a given long-term horizon (e.g. 2050). The problem consists in minimizing the sum of two terms:

$$\min_{\kappa}\left\{C^{capex}(\kappa) + \max_{\eta} C^{opex}(\kappa,\eta)\right\} \quad \text{(CEM)}$$

where:

(a) κ denotes a vector containing the investment capacities either on generation technologies at each node of the network or on some lines of the transmission network.

(b) $C^{capex}(\kappa)$denotes the annualized investment cost induced by installing the capacity κ in the electrical system.

(c) $C^{opex}(\kappa,\eta)$ denotes the expected operation cost of the system with the given installed capacity κ on the typical time horizon (for instance year 2050), under the assumption of scenario η.

Additional constraints can be included:

1. <u>Each region can produce the amount of energy required to meet the demand</u>.

   For each zone *Z*, for each scenario *j*

$$\sum_{t,i\in Z} \kappa_i P_{i,t}^{max} \sum_j \alpha_{i,t,j} \geq \sum_{t,j} D_{t,j}^{Z} \quad (1.1)$$

$$\sum_{t,i\in Z,j} \kappa_i P_{i,t,j}^{max} \geq \sum_{t,j} D_{t,j}^{Z} \quad (1.2)$$

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

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

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

   κ_i : number of units of techno i in region z (it is a variable for the CEM).

2. <u>Each region must reach a target in terms of RES share (including hydro)</u>

$$\sum_{t,i\in ENR\cap Z,j} \kappa_i P_{i,t}^{max} \alpha_{i,t,j} \geq \rho^Z \sum_{t,i\in Z,j} \kappa_i P_{i,t}^{max} \alpha_{i,t,j} \quad (2.1)$$

$$\sum_{t,i\in ENR\cap Z,j} \kappa_i P_{i,t,j}^{max} \geq \rho^Z \sum_{t,i\in Z,j} \kappa_i P_{i,t,j}^{max} \quad (2.2)$$

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

The 2 constraints (1 = 1.1 and 1.2) and (2 = 2.1 and 2.2) cannot be used together.

2 Seasonal Storage Model

The Seasonal Storage Model solves a mid-term problem, where mid-term usually stands for annual because large storages which are mainly hydropower reservoirs are managed seasonally (inflows and electricity demand usually follow an annual seasonality). This problem consists in evaluating an approximation of the expected operation cost, $C^{opex}(\kappa, \eta)$, for a given vector of installed capacity, κ, under the assumption of a set η of scenarios.

The mid-term horizon is a set of stages $S = \{s_0, s_1, \dots s_n\}$ (eg. weeks), subdividing the typical period (e.g. 1 year) on which operation costs are evaluated. Each stage is divided in time steps $\{t_0, t_1, \dots t_n\}$ (e.g. 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 (see below for more information), aiming at minimizing the sum of operation costs on each stage s:

$$C^{opex}(\kappa) = \min_{x \in X} E\left[\sum_{s \in S} C_s^{opex}(x_s)\right] \quad (3)$$

Where:

• $\mathrm{x} = (x_s)_{s \in S}$ 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 depend on the past realizations of uncertainties and on the future expected uncertainties represented by the cost-to-go functions that are iteratively computed by the SSV giving the minimum future operational expected cost.

X is the feasible set associated with operation decisions. We also emphasize the presence of dynamical constraints (water flows between several hydropower reservoirs that relate reservoir levels between two time steps, 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 κ and on uncertainties revealed at stage s (demand, inflows, intermittent generation): note the expectation E appearing in (3) .

This problem is solved by time decomposition using stochastic dynamic programming. At each stage s, a transition problem is solved, involving the deterministic operational cost of stage s C_s^{opex} and the cost-to-go function. The transition cost is evaluated by the UC Model (see below). Indeed, each stage represents the time horizon for which we consider that there are no uncertainties. For example, using weekly stages, we consider that at a given time, all data (inflows, demand) is perfectly forecasted for the next week. If the duration of the stage also corresponds to the management time frame of other production assets, such has small hydropower reservoirs, all the better.

3 Unit Commitment Model (UC)

The unit commitment problem (UC) solves the short-term horizon problem (short-term meaning “corresponding to a stage” usually weekly), where operational decisions are provided at one stage s

$\in S$, in a deterministic setting, considering the expected future "value" that seasonal storage units can bring to the system via the cost-to-go function. The UC is used in two contexts.

(a) The UC optimization mode solves the transition problem of SSV with some approximations that are required to make the problem tractable. It is intended to provide cutting plane approximations of cost-to-go functions. Note that the associated operational decisions may be infeasible due to the approximation, which is not usually that big of the problem, the objective being to compute the cost-to-go functions. The advantage is that the UC optimization mode should run reasonably fast.

(b) The UC simulation mode solves the transition problem, without any simplification of modelled operational constraints. This mode is intended to provide a feasible generation dispatch, on a given stage. It uses the cost-to-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 UC simulation mode could be significantly greater than that to run the UC optimization mode, since no approximation is made.

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

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

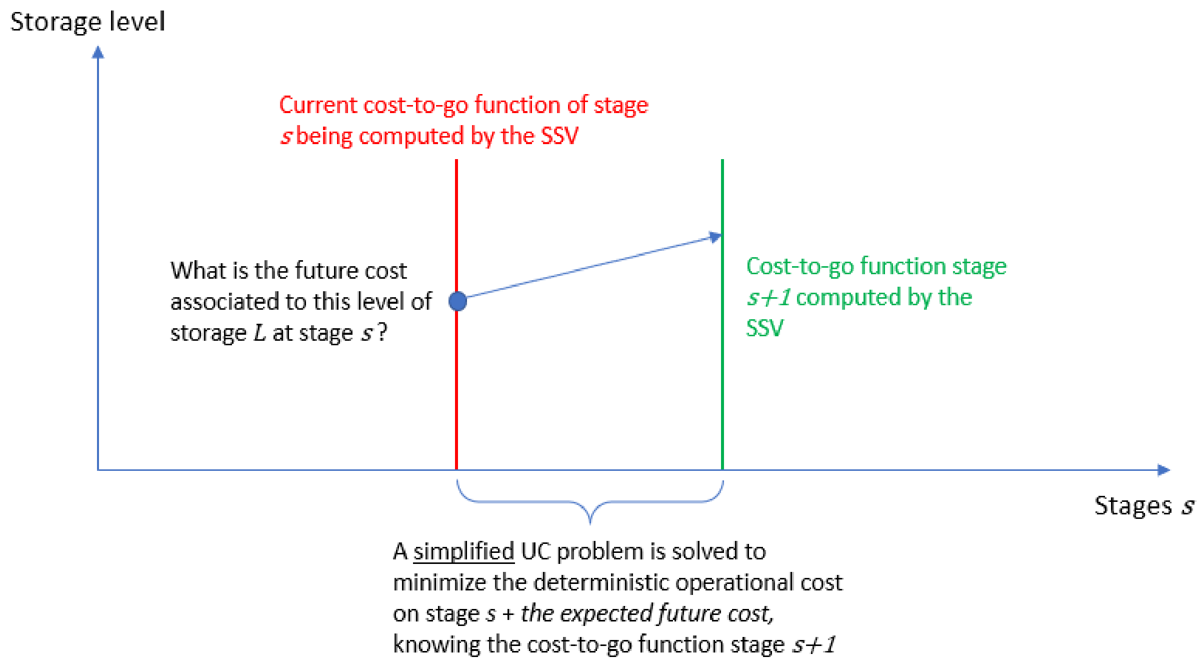
- Dynamic operation constraints of power plants (ramping constraints, minimum shut-down duration, …)
- Dynamic operation of storage (including battery-like storages and complex hydro-valleys modelling)
- Demand-Response (including e.g. household dynamic consumption load-shifting or load curtailment)

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 (see the data format guide for more details on partitions and zones).

4 Illustrations

The following figure illustrates the SSV et UC presented above. When managing storages, such as hydropower plants associated to large reservoirs under uncertainties (inflows, RES generation, demand level…), one must answer the following question: should I use one unit of storage now (= on the current stage s) or keep it for a later use due to future uncertainties? To do so, one must know the expected future opportunities that a given amount of storage represent: this is the role of the *cost-to-go* functions that represent the expected future system cost for a given level of storage at a given stage s. The cost-to-go functions are computed by the SSV using the UC (see paragraph (a) of section 3).



Note that this illustration corresponds to stochastic dual programming for only one storage. The SSV uses Stochastic Dual Dynamic Programming which iteratively builds (cutting plane) approximations of the cost-to-go functions for all storages using forward and backward passes.

In simulation mode, the principal is the same: all cost-to-go functions for each stages s have been computed by the SSV: transition problems on each stage are computed in a forward manner.