PSR

RECENT APPLICATIONS OF MULTISTAGE STOCHASTIC OPTIMIZATION TO POWER SYSTEM PLANNING AND OPERATIONS

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CORE 50 years

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PSR

Global provider of analytical solutions and consulting services in electricity and natural gas since 1987

Our team has 54 experts (17 PhDs, 31 MSc) in engineering, optimization, energy systems, statistics, finance, regulation, IT and environment analysis

Overview

- Current stochastic optimization applications

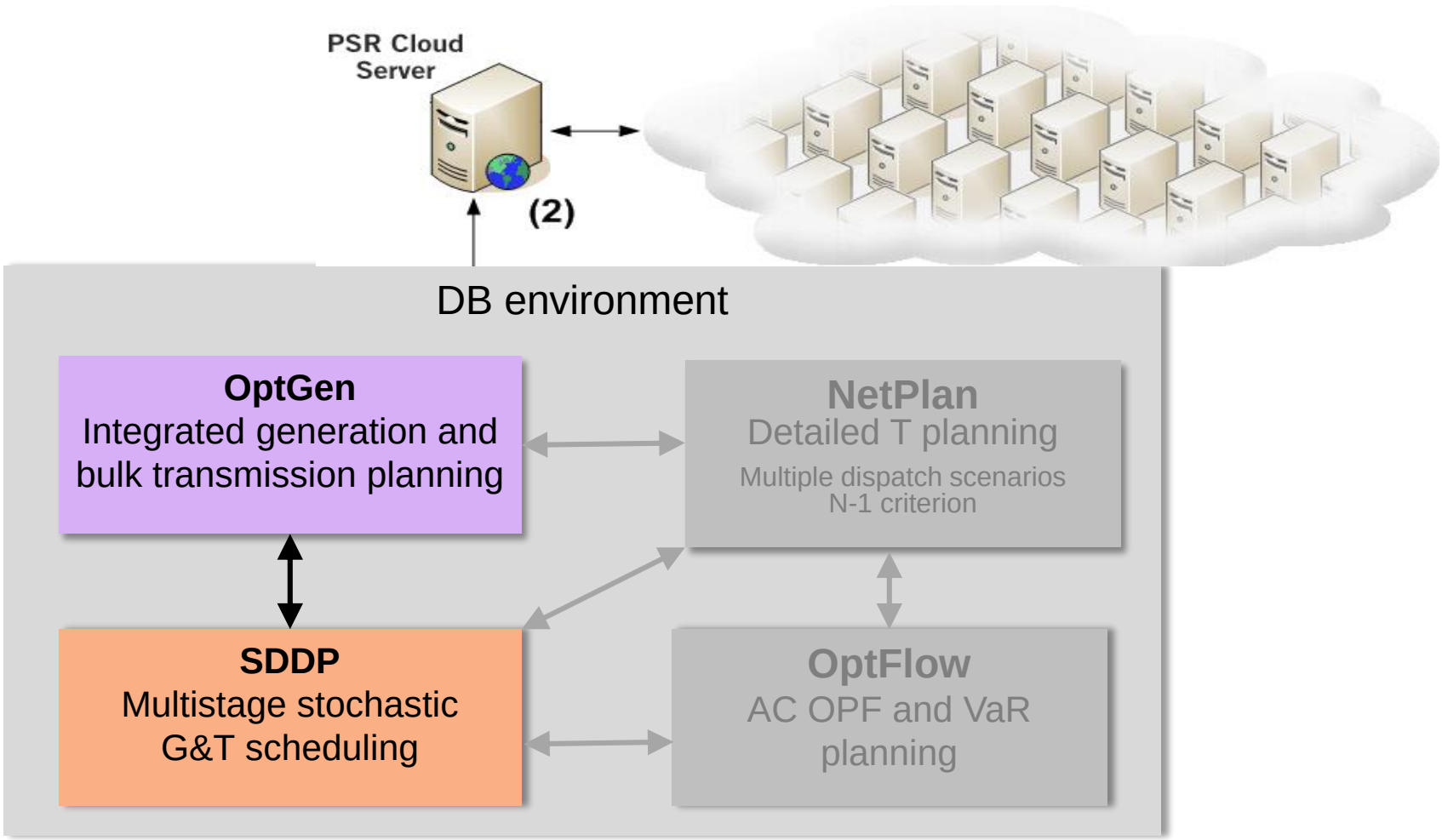
  - Multistage G&T scheduling – w/ *Ricardo Perez*
  - Integrated G&T expansion planning – *w/ Lucas Okamura*

- Recent developments

  - Analytic operating cost function for multiscale dispatch – w/ *Camila Metello*
  - Risk aversion modelling (CVaR and robust approaches) – w/ *L.C.Costa*

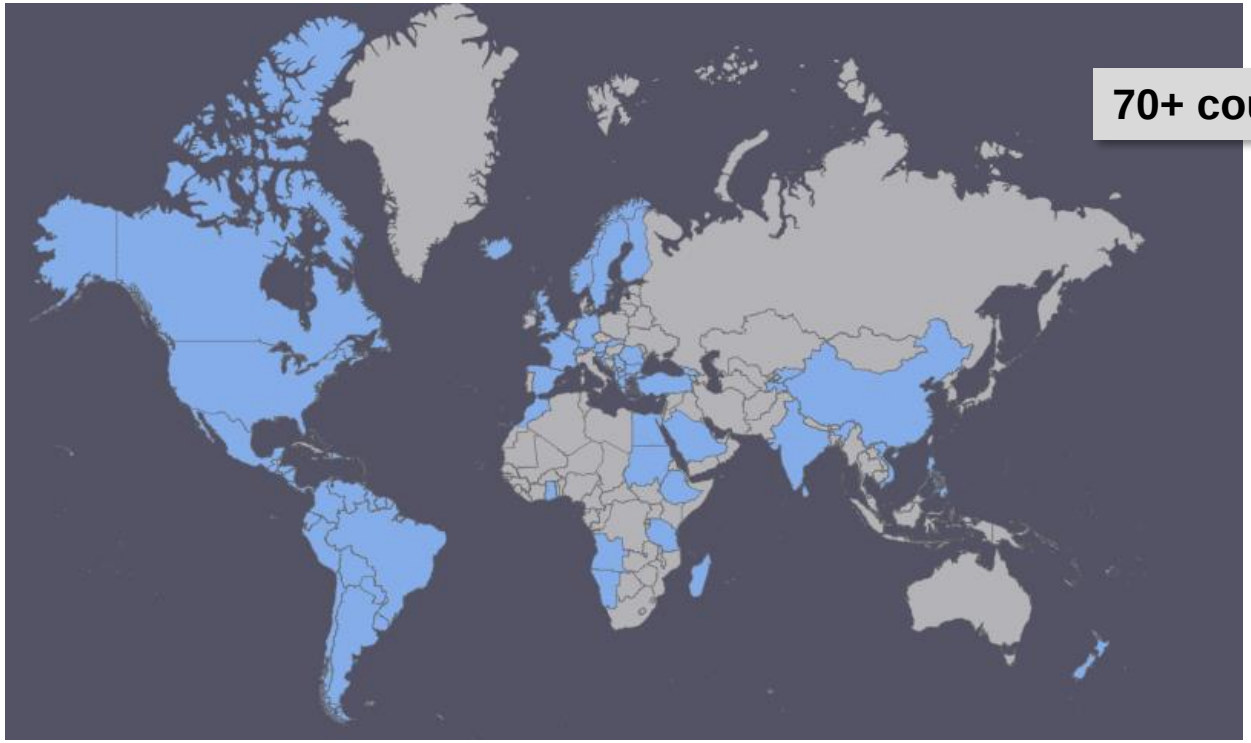
  - Parameter uncertainty of stochastic models – w/ *Bernardo Bezerra*

Current stochastic optimization tools



All models represent complex hydrothermal systems with renewable generation, transmission networks, price-responsive loads, gas pipelines and fuel storage

Application of stochastic models



- **Americas**: all countries in South and Central America, United States, Canada and Dominican Republic
- **Europe**: Austria, Spain, France, Scandinavia, Belgium, Turkey and the Balkans region
- **Asia**: provinces in China (including Shanghai, Sichuan, Guangdong and Shandong), India, Philippines, Singapore, Malaysia, Kirgizstan, Sri Lanka, Tajikistan and Vietnam
- **Oceania**: New Zealand
- **Africa**: Morocco, Tanzania, Namibia, Egypt, Angola, Sudan, Ethiopia and Ghana

SDDP: stochastic multistage G&T scheduling

- Weekly or monthly time steps; 25+ years horizon
  - Intra-stage: 5-21 load blocks to 168-730 hours
- Detailed generation modeling: hydro, fossil fuel plants and renewables
- Interconnections or full transmission network: DC with losses and AC
- Price-responsive load by region or by bus
- Fuel production, storage and transportation network
- Water-energy nexus: water supply, irrigation, flood control etc.

Application example

Power Market Trader

Nordic power market outlook

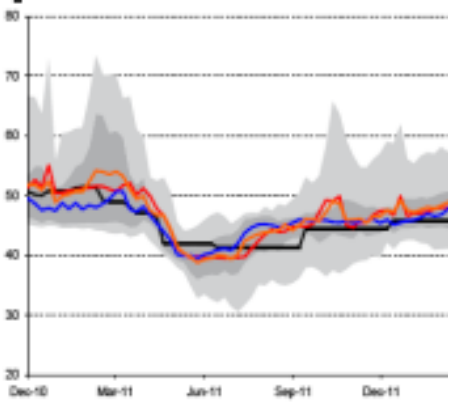
ENERGY

TO THE POINT

This model run is based on hydrology/ weather forecasts as of Monday November 8. Fuel prices and Continental power prices are closing prices from Friday November 5.

Since the model run two weeks ago the hydro balance is slightly worsened (-2 TWh). Over the course of the same period Continental power prices has moved slightly down (EEX Q1-11 -€0.5/MWh) and SRCM coal is unchanged. The very close front of the curve is slightly down whereas the February and March prices are up. The front year is unchanged.

Figure 1: SDDP system price forecast. 2010 - 2



The new SDDP Nordic

3 YEAR FORECASTS WITH IMPROVED STACK AND HYDROLOGY

In April 2008 we presented the first SDDP forecast for the Nord Pool market at the annual Montel spring conference. Our estimate was very bearish for May compared with the market, but more bullish later in the summer. It turned out that the delivered price for May was even lower than we forecasted. After that head start our medium term forecast have become an important reference for the Nordic market, most recently when the market really turned bearish this June.

Our goal is to always perform better and deliver better services to our clients, and over the years we have seen some areas of improvement. Most notably is the new price areas in both Norway and Sweden, but we also wanted a better coupling between our hydrological (HBV) models and a full revision of the stack.

Hence, over the last year we have put a lot of effort in recalibrating the SDDP model at the same time as publishing our weekly forecast. Last week we published our first forecast with the recalibrated SDDP Nordic. The SDDP methodology is developed by PSR in Brazil, a strategic partner of Thomson Reuters.

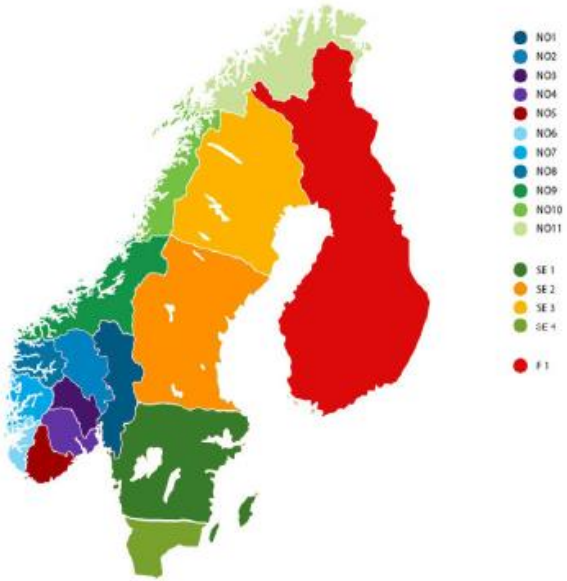


Figure 1: New hydro regions as modeled in the. HBV and SDDP models. Notice that the hydro regions for Norway are not identical to the price regions (NO1-5).

NEW FEATURES

The main new feature of the new SDDP model is a detailed modeling of all the 12 Nord Pool price areas. The historical inflow series have been updated as well, based on the years 1981 to 2007. However, from week 1 to week 40 in the SDDP forecast we use the latest HBV long term forecast based on the latest EC00 ens the first two weeks and historic temperatures and precipitation thereafter. There is good match between the price areas and the hydro regions, although there are some minor deviations between NO5 and the corresponding hydro region (NO6 in the map over hydro regions).

We have updated the load using weekly load levels that has been temperature corrected against a temperature normal for each region (for NO1-5 and SE1-4 we have used one representative station for each of the areas).

Stochastic optimization model

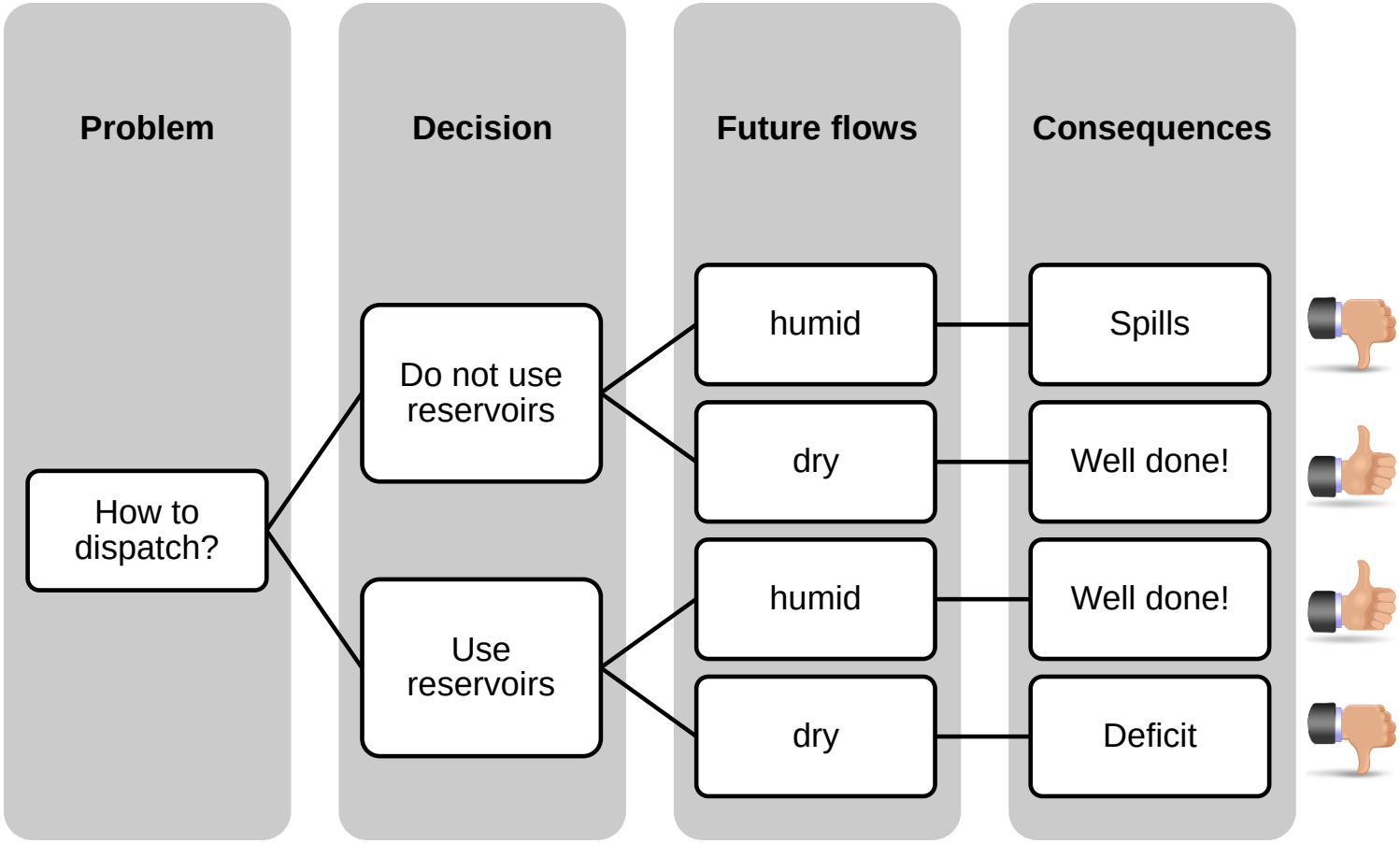
Solution algorithm: stochastic dual dynamic programming (SDDP)

- Avoids “curse of dimensionality” of traditional SDP $\Rightarrow$ handles large systems
- Suitable for distributed processing

Stochastic parameters

- Hydro inflows and renewable generation (wind, solar, biomass etc.)
  - Multivariate stochastic model (PAR(p))
    - Inflows: macroclimatic events (El Niño), snowmelt and others
    - Spatial correlation of wind, solar and hydro
    - External renewable models can be used to produce scenarios
- Uncertainty on fuel costs
  - Markov chains (hybrid SDDP/SDP model)
- Wholesale energy market prices
  - Markov chains
- Load variability and equipment outages
  - Monte Carlo sampling

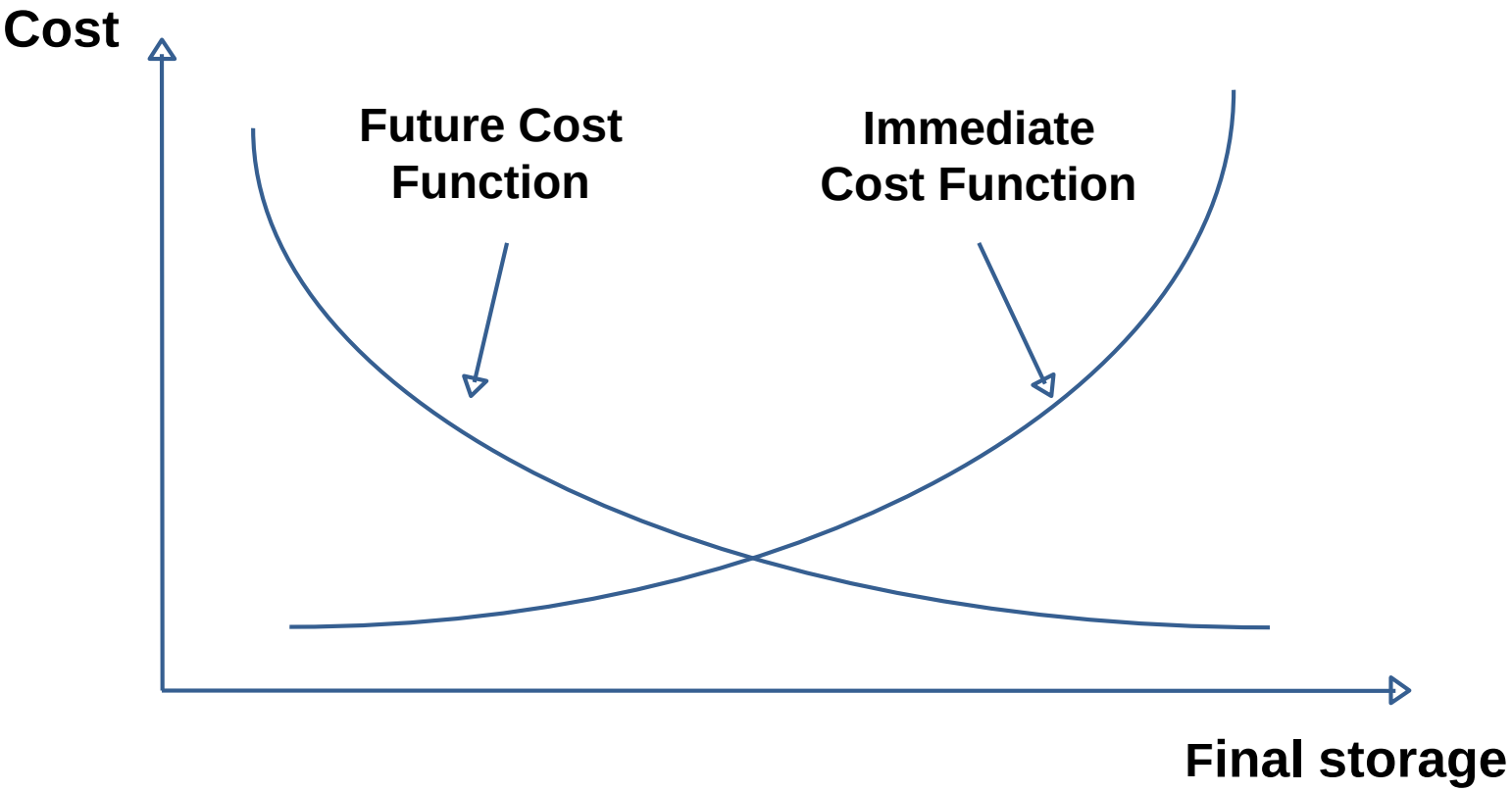
The stochastic optimizer's dilemma



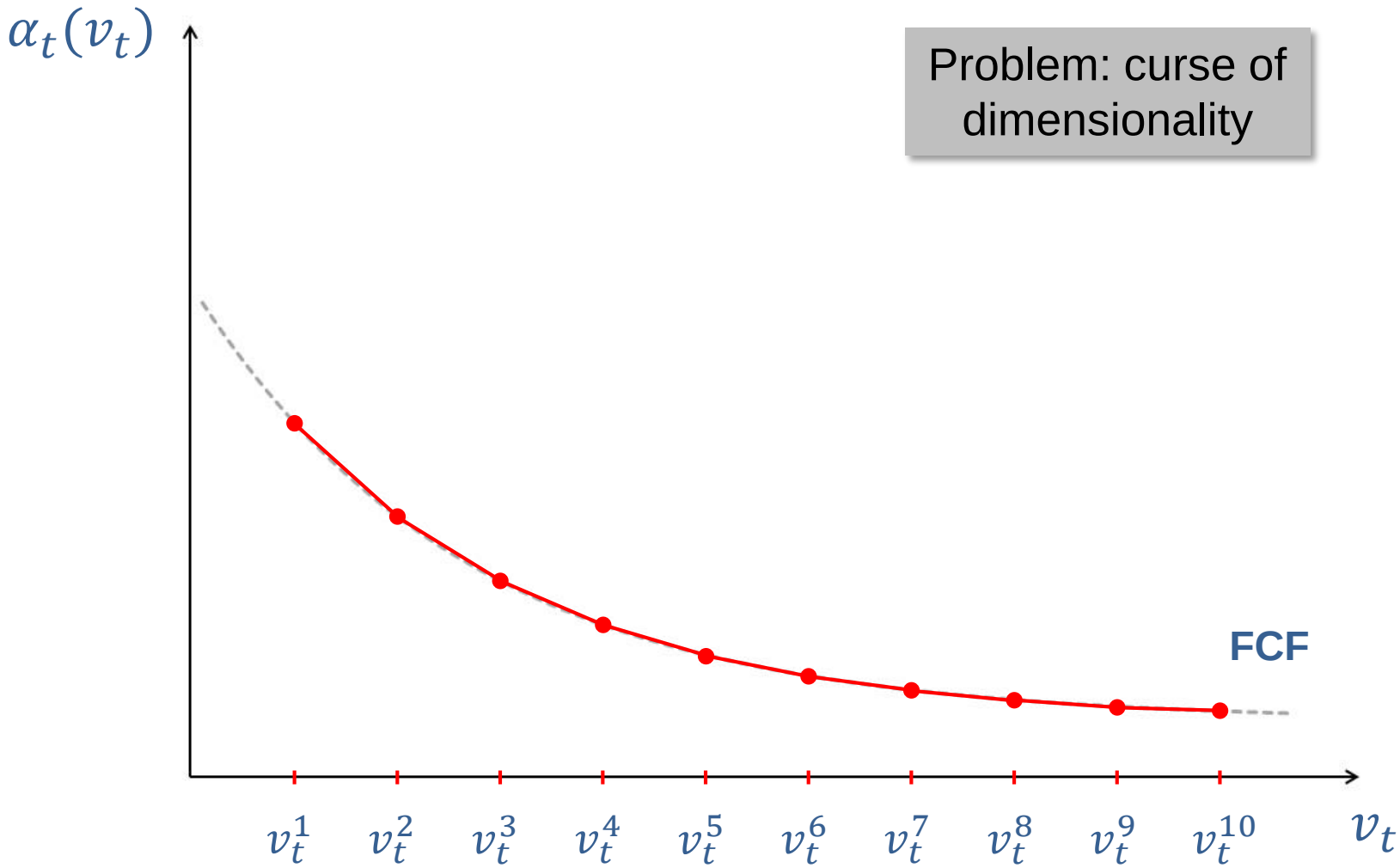
Challenge: a real life generation scheduling problem may have a five-year horizon (60 monthly steps)
⇒ The decision tree would have 10^{100} nodes

Stochastic Dynamic Programming

- State space formulation
- Decomposition in time stages

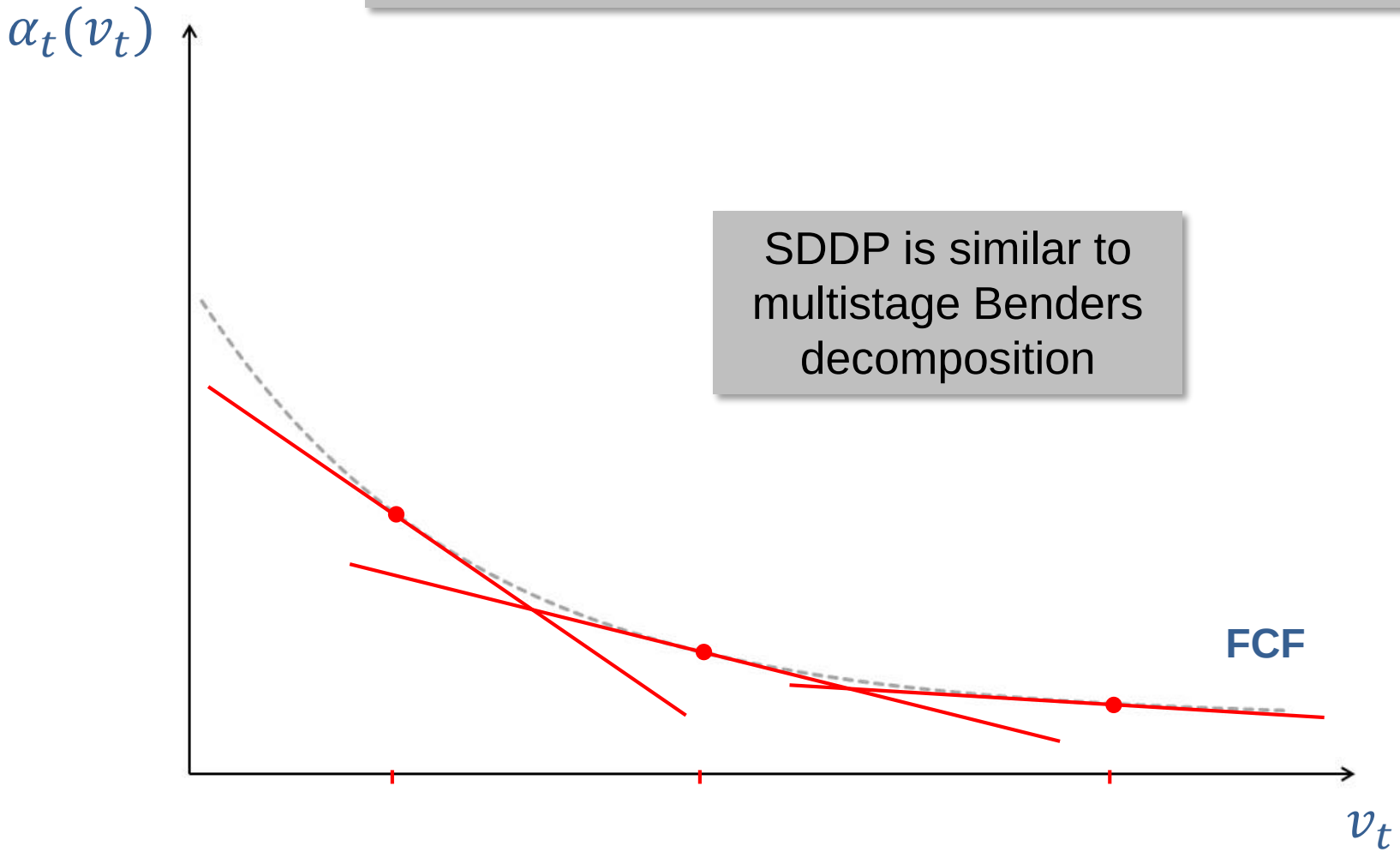


Traditional approach: discretize states



Stochastic Dual DP

1. Simulation of system operation to find “interesting” states
2. Piecewise linear approximation of FCF



SDDP is similar to multistage Benders decomposition

One-stage operation problem (simplified)

- Objective function (min immediate cost + future cost)

$$Min \ \sum_{\tau} \sum_{j} c_j g_{t\tau j} + \alpha_{t+1}(\{v_{t+1,i}\})$$

LP solved by relaxation of FCF constraints (very important for computational efficiency)

- Storage balance

$$v_{t+1,i} = v_{t,i} + a_{t,i} - u_{t,i} \quad \forall i = 1, \dots, I$$

- Power balance

$$\sum_{\tau}\left(\sum_{j} g_{t\tau j} + \sum_{i} e_{t\tau i}\right) = \hat{d}_{t\tau} - \sum_{n} \hat{r}_{t\tau n} \quad \forall \tau = 1, \dots, \mathrm{T}$$

- Future cost function (FCF)

$$\alpha_{t+1} \geq \sum_{i} \pi_{vi}^{k} v_{t+1,i} + \sum_{i} \pi_{ai}^{k} a_{t+1,i} + \delta^{k} \quad \forall k = 1, \dots, K$$

SDDP characteristics

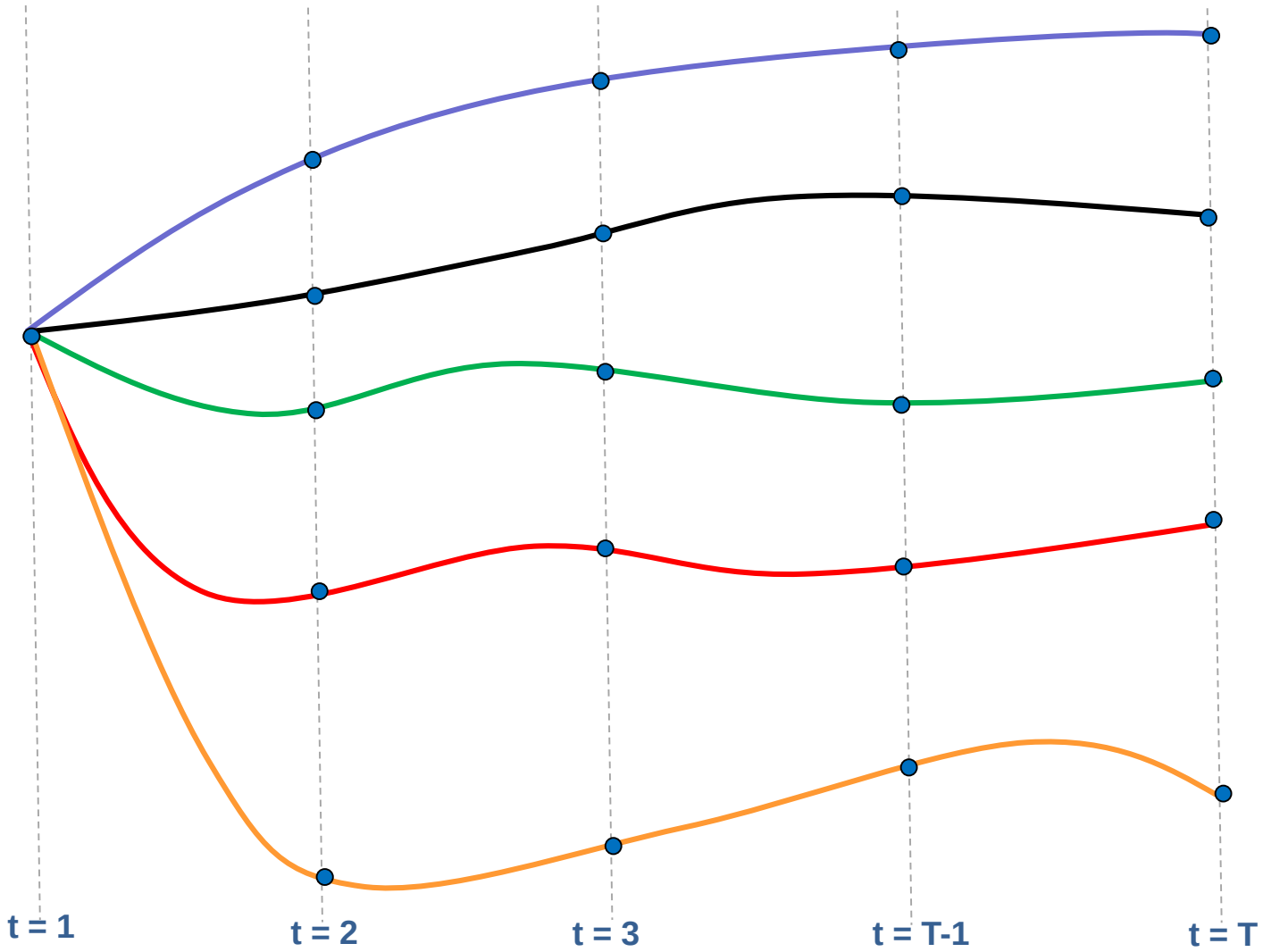
Iterative procedure

1. forward simulation: finds new states & upper bound (UB)
2. backward recursion: updates FCFs & lower bound (LB)
3. convergence check (LB in UB's confidence interval)

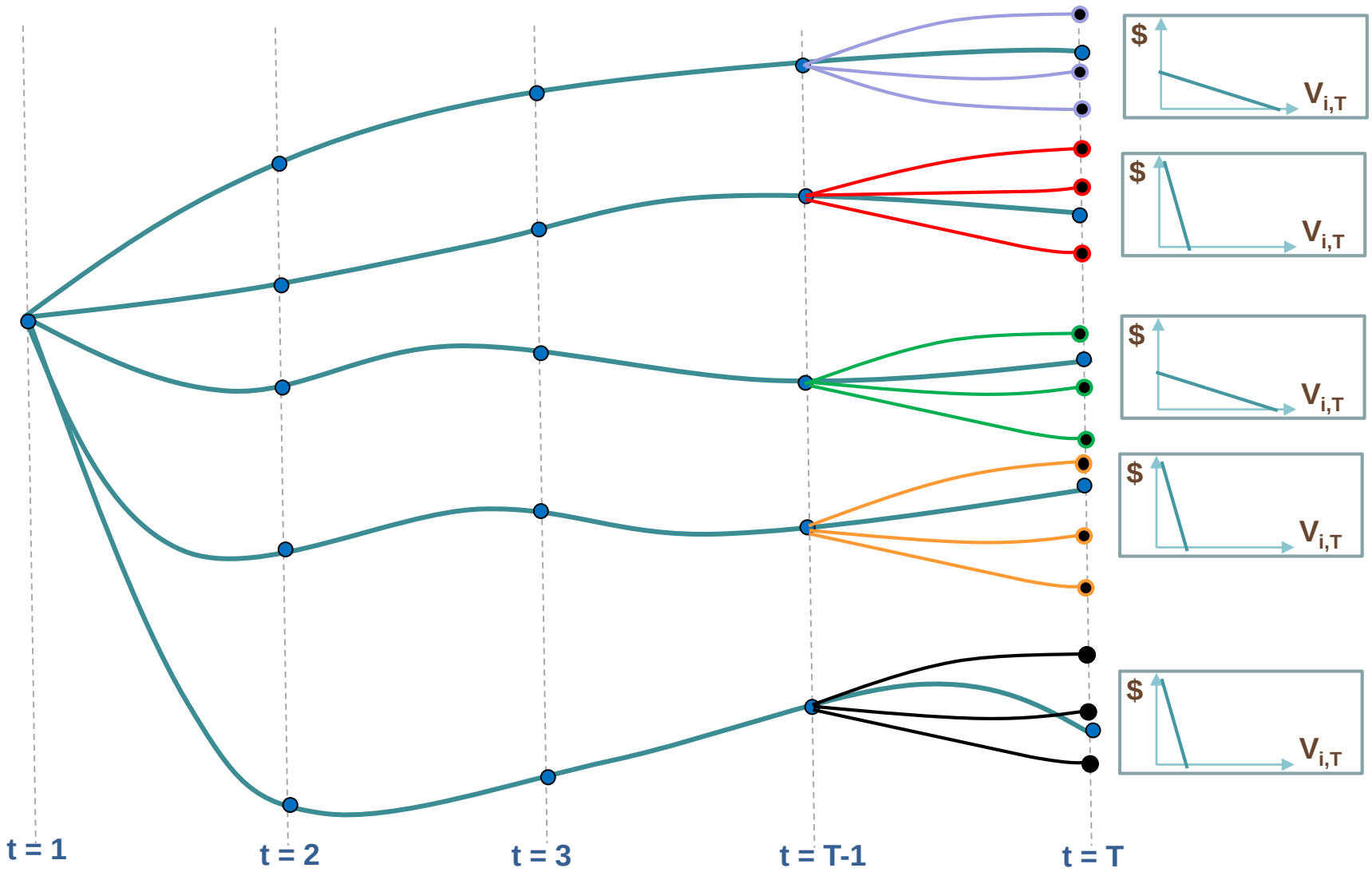
Distributed processing

- The one-stage subproblems in both forward and backward steps can be solved simultaneously, which allows the application of distributed processing
- SDDP has been running on computer networks since 2001; from 2006, in a cloud system with AWS
  - We currently have 500 virtual servers with 16 CPUs and 900 GPUs each

SDDP: distributed processing of forward step



SDDP: distributed processing of backward step



Example of SDDP run with distributed processing

- Installed capacity: 125 GW
- 160 hydro (85 with storage), 140 thermal plants (gas, coal, oil and), 8 GW wind, 5 GW biomass, 1 GW de solar
- Transmission network: 5 thousand buses, 7 thousand circuits

State variables: 85 (storage) + 160 x 2 = 320 (AR-2 past inflows) = 405

Monthly stages: 120 (10 years)
Load blocks: 3

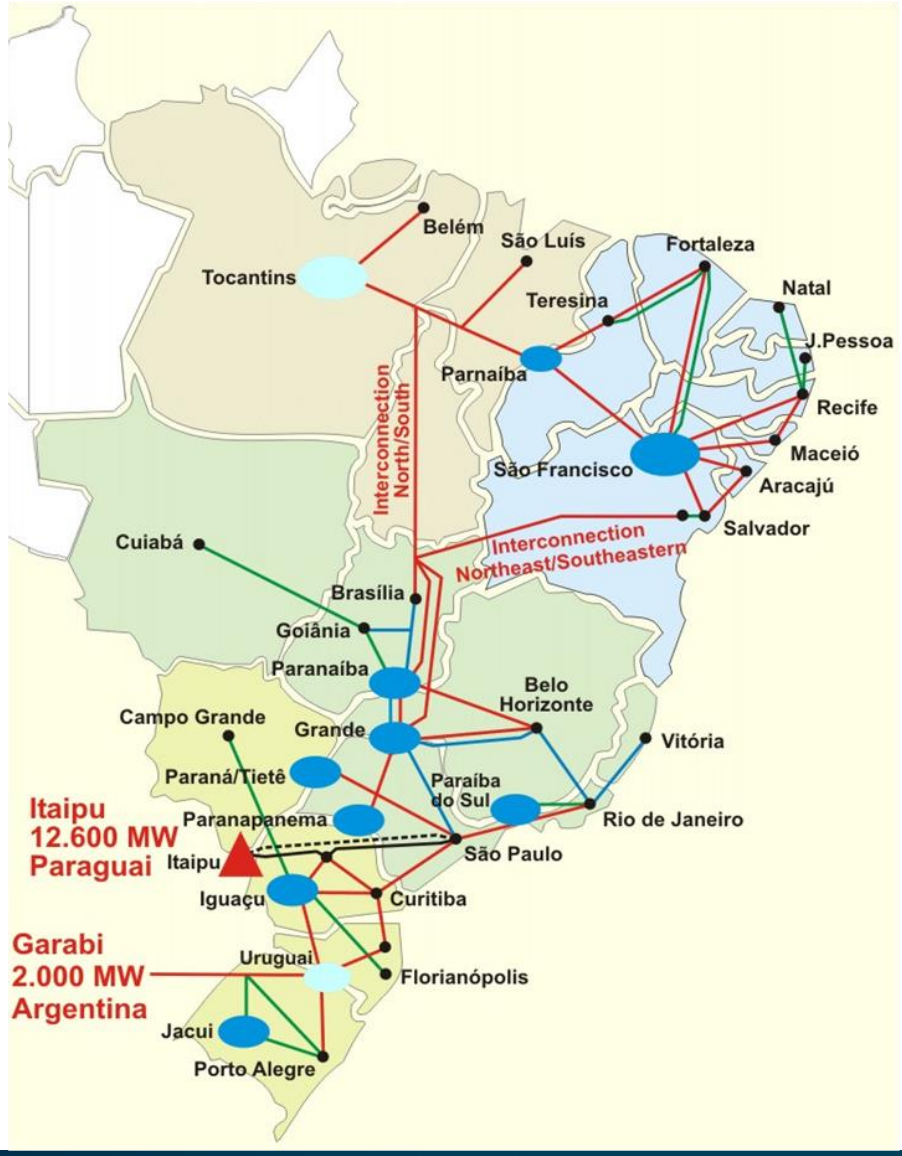
Forward scenarios: 1,200

Backward branching: 30

LP problems per stage/iter: 36,000

Number of SDDP iterations: 10

Total execution time: 90 minutes
25 servers with 16 processors each



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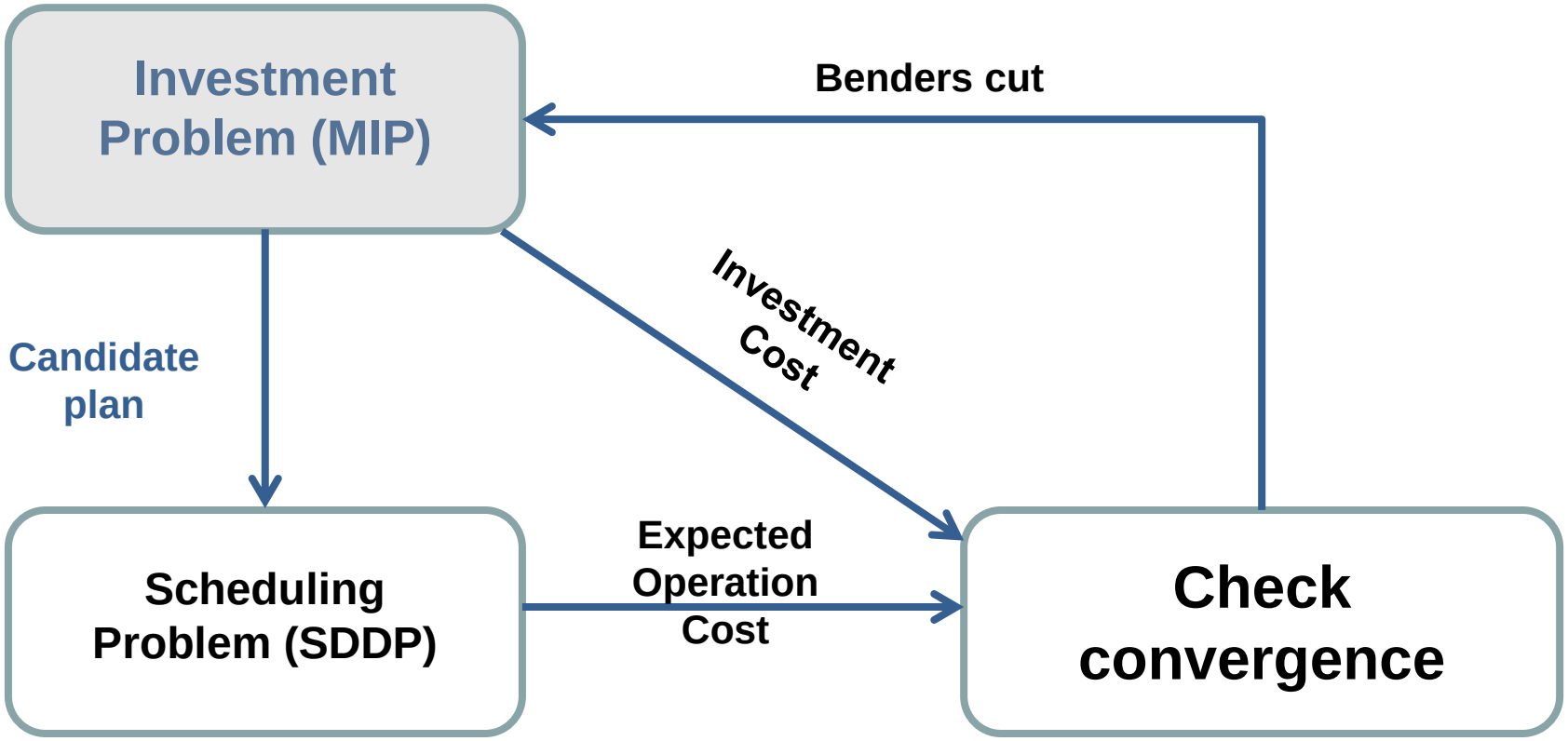
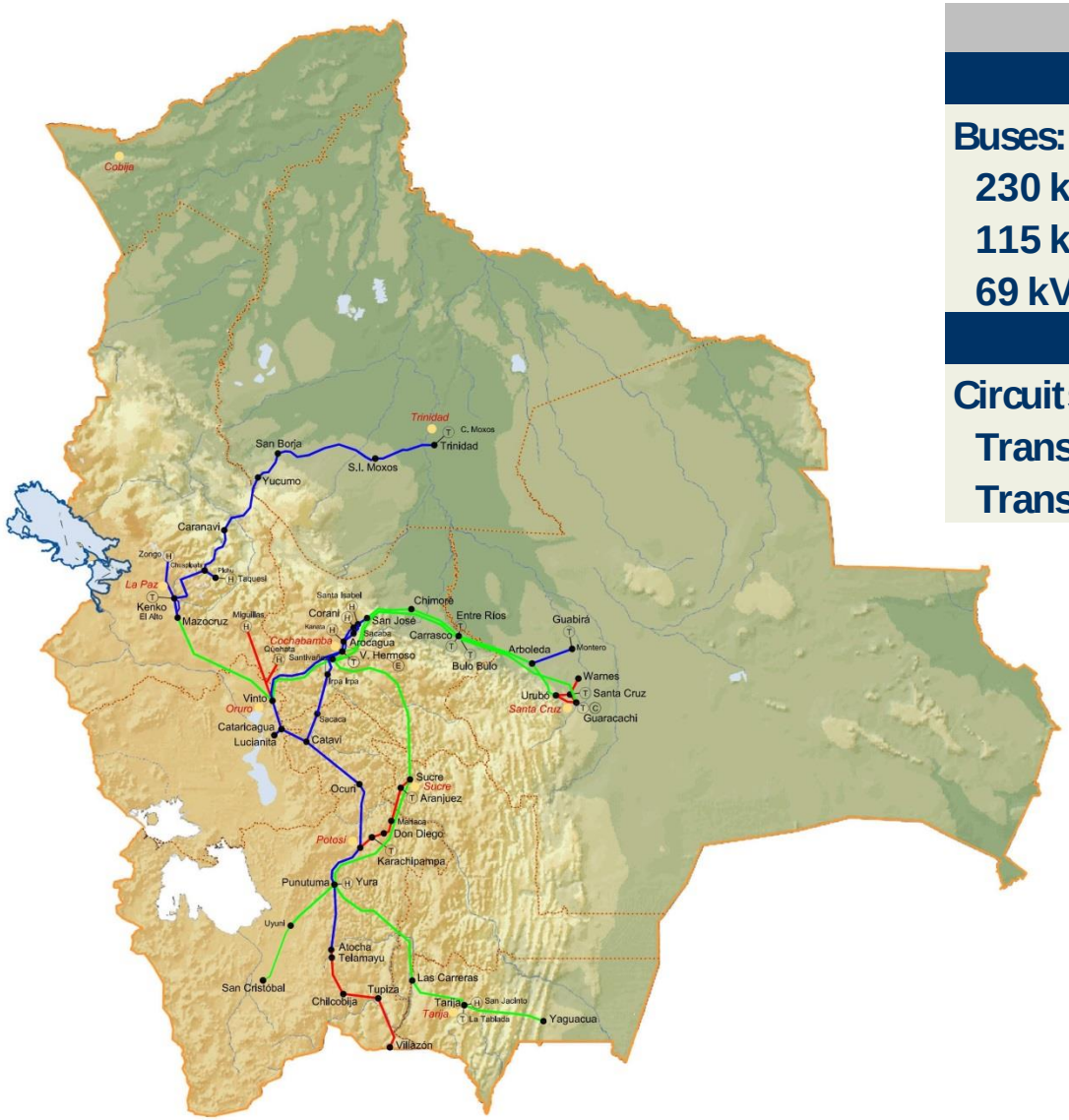
  - Parameter uncertainty of stochastic models
  - Generation expansion strategies

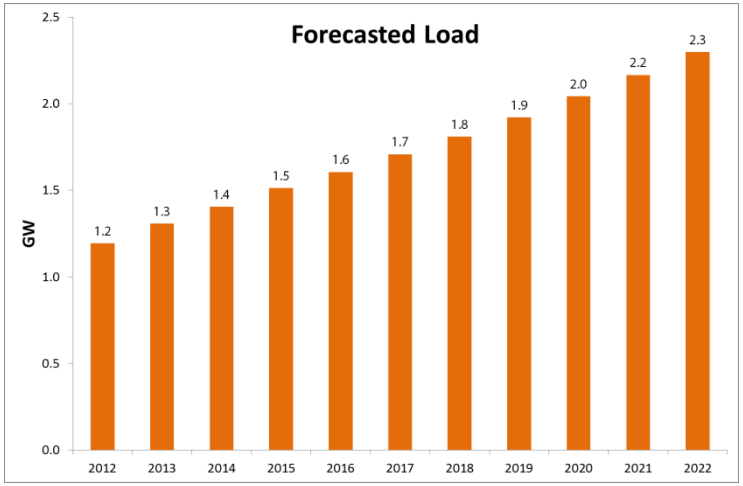
Optgen: generation & transmission planning



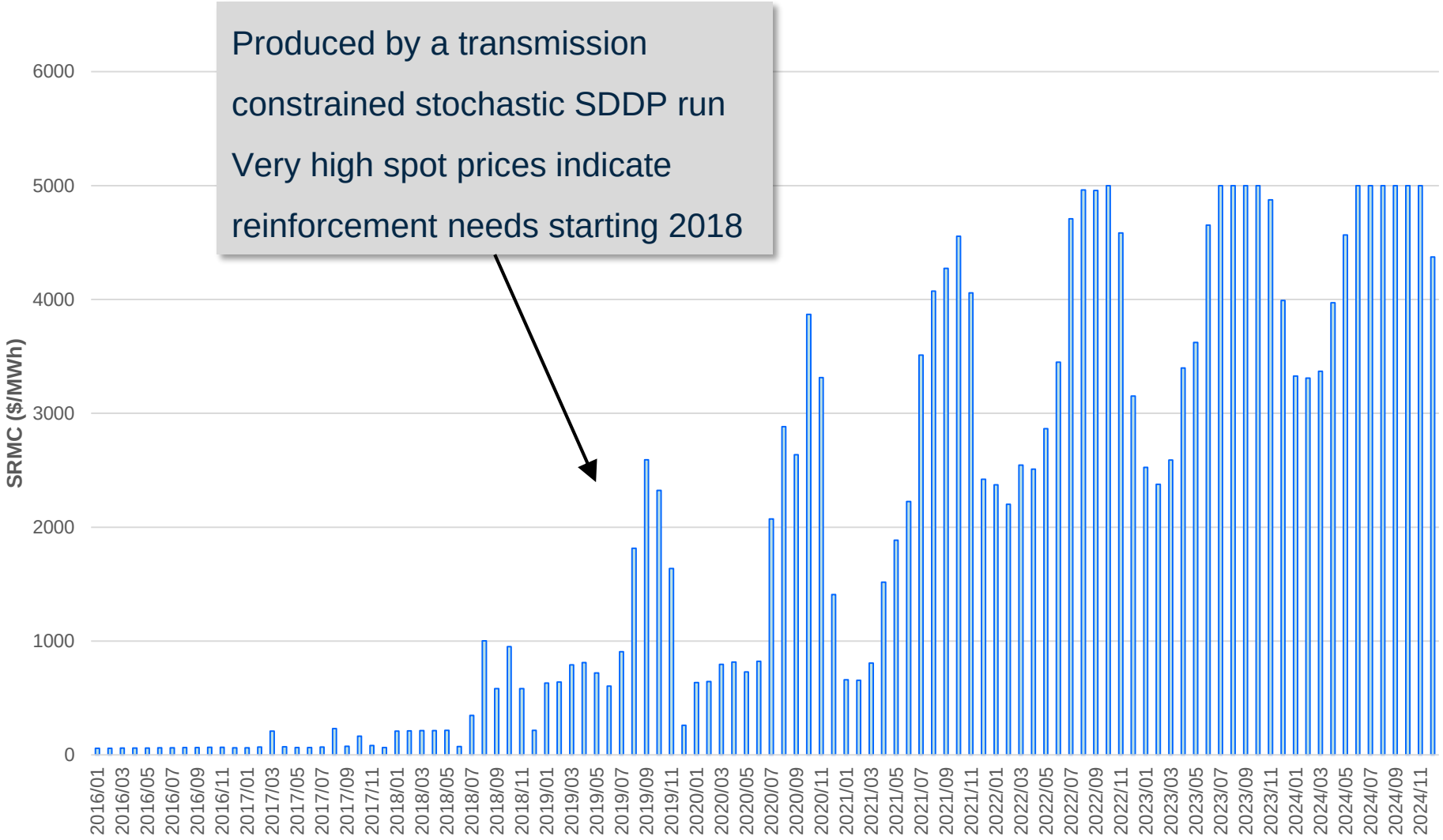
Example: Bolivia



Transmission System	
Buses:	**141**
230 kV	**29**
115 kV	**72**
69 kV	**40**
Circuits	**127**
Transmission lines:	**100**
Transformes:	**27**



System spot prices – no reinforcements



Generation & transmission expansion plan

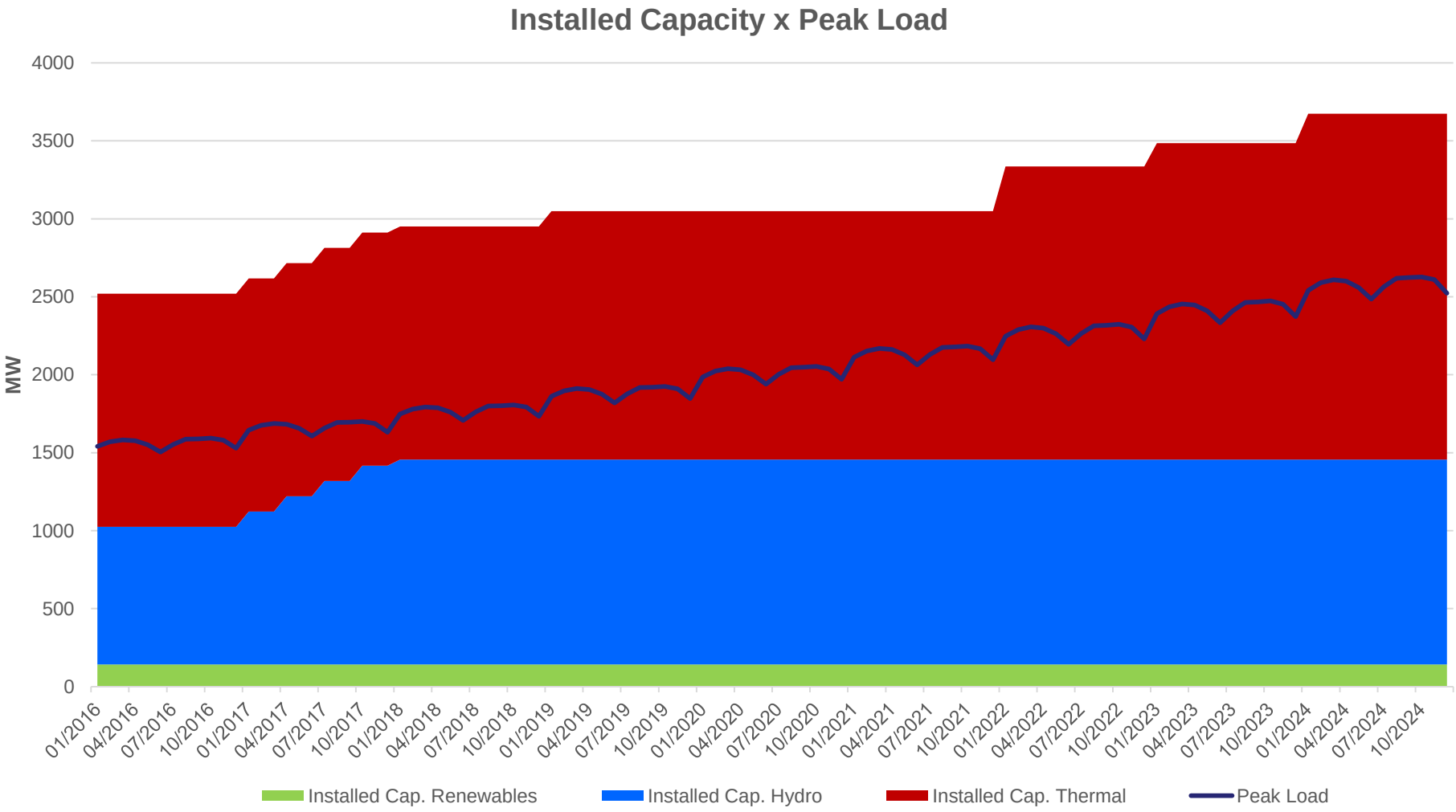
Study parameters

- Horizon: 2016-2024 (108 stages)
- 123 candidate projects per year (x 9 years)
  - 17 thermal plants (natural gas, combined and open cycle)
  - 7 hydro plants
  - 7 renewable projects (wind farms and solar)
  - 92 transmission lines and transformers

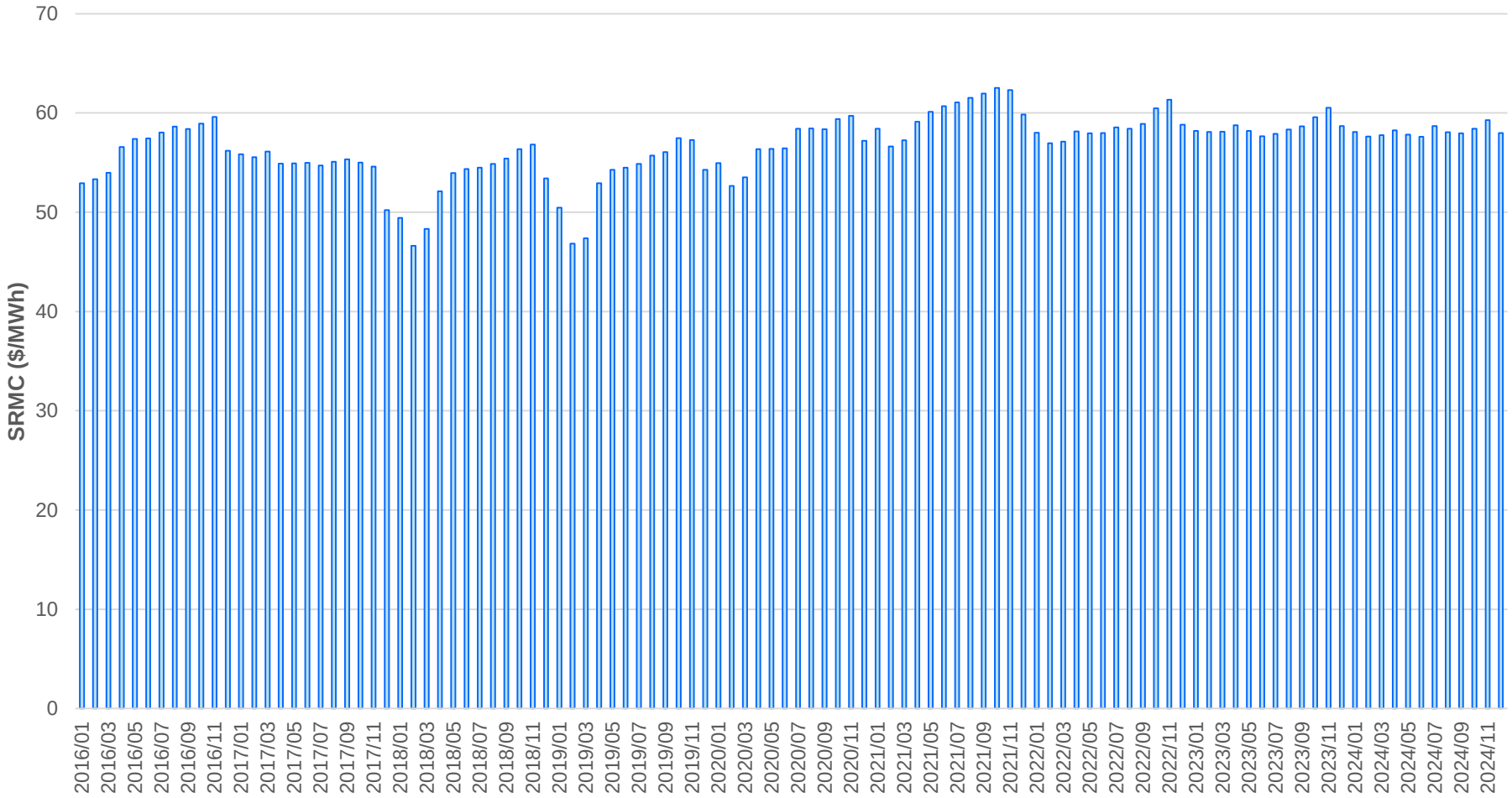
Computational results

- Number of Benders iterations (investment module): 53
- Average number of SDDP iterations (stochastic scheduling for each candidate plan in the Benders scheme): 5
  - Forward step: 100 scenarios
  - Backward step: 30 scenarios (“branching”)
- Total execution time: 2h 37m
  - 2 servers x 16 processors

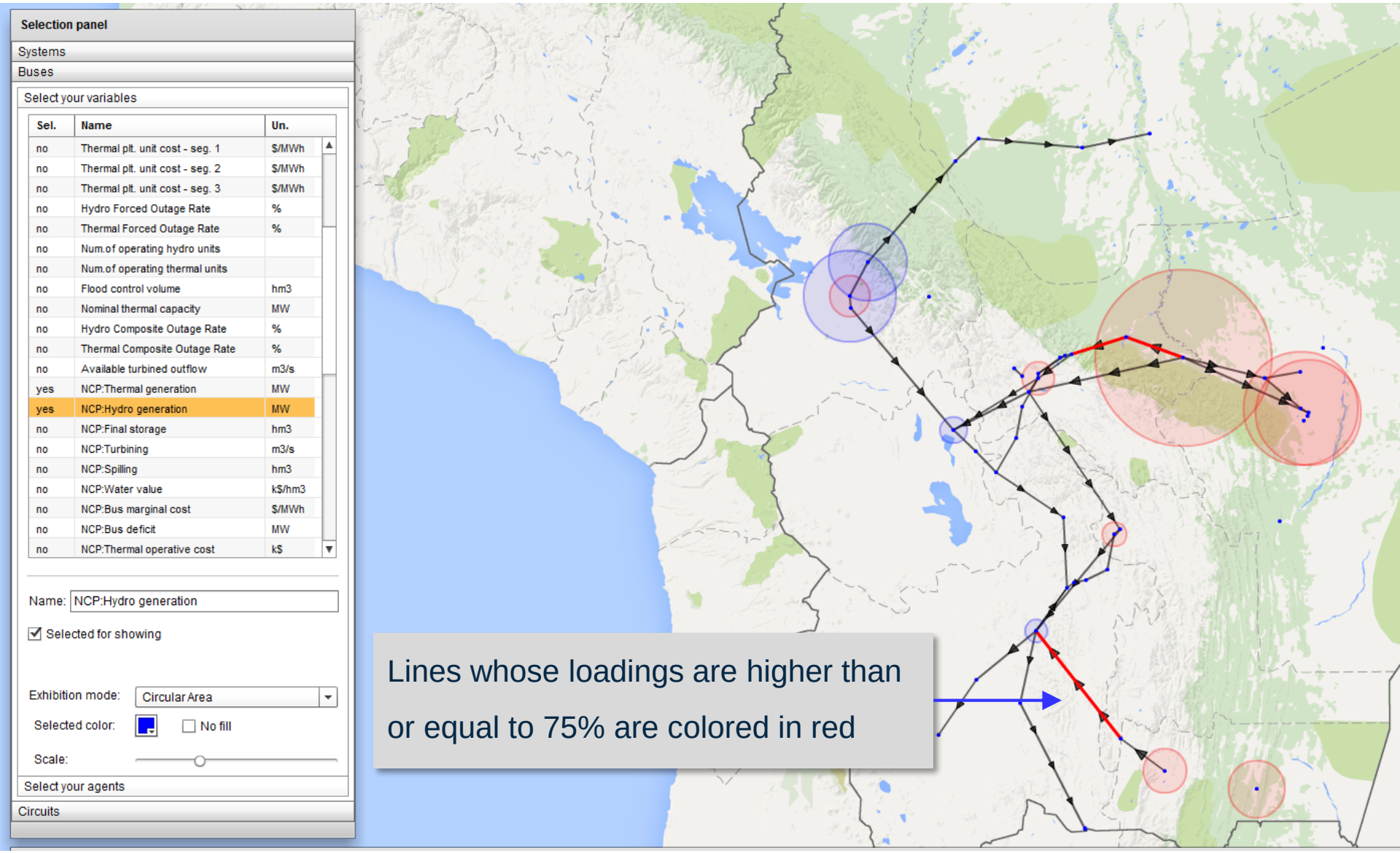
Optimal generation expansion plan



Spot prices - after optimal expansion



Power flows and generation (after reinforcement)



Lines whose loadings are higher than or equal to 75% are colored in red

Conclusions: current stochastic models

- Extensive experience with the application of stochastic scheduling and planning models to large-scale systems
  - SDDP/SDP and Benders decomposition
- Detailed modeling of generation, transmission, fuel storage and distribution, plus load response
- Multivariate AR models + plus Markov chains used to represent uncertainties on inflows, renewable production, fuel costs, equipment availability and load
- Distributed processing is effective for reducing run times
  - With cloud computing, it is also cost-effective

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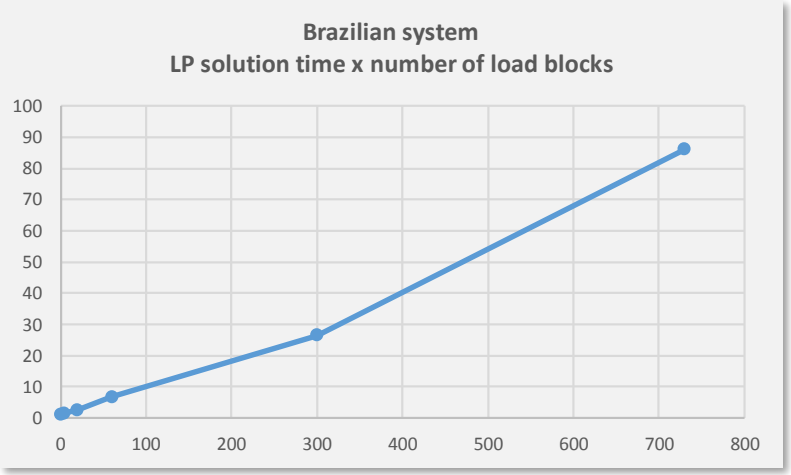
Motivation

- The very fast growth of renewables has raised concerns about operating difficulties when they are integrated to the grid
  - For example, “wind spill” in the Pacific Northwest, need for higher reserve margins due to the variability, hydro/wind/solar portfolio etc.
- The analysis of these issues requires an hourly (or even finer) resolution in the intra-stage operation model

  $\Rightarrow$ much higher execution times



Idea: analytical representation of immediate cost

- Objective function (min immediate cost + future cost)

$$Min\ \beta_t(e_t) + \alpha_{t+1}(\{v_{t+1,i}\})$$

- Storage balance

$$v_{t+1,i} = v_{t,i} + a_{t,i} - u_{t,i} \quad \forall i$$

- Future cost function

$$\alpha_{t+1} \geq \sum_i \pi_{vi}^k v_{t+1,i} + \sum_i \mu_i^k a_{t+1,i} + \delta^k \quad \forall k$$

- Immediate cost function

$$\beta_t \geq \pi_e^p e_t + \delta^p \quad \forall p = 1, \dots, P$$

- Problem size is the same for any number of load blocks
- The same relaxation techniques used for α_{t+1} can also be applied to β_t

Pre-calculation of $\beta_t(e_t)$: single area

$$\beta_t(e_t) = Min \sum_\tau \sum_j c_j g_{t\tau j}$$

$$\sum_\tau e_{t\tau} = e_t$$

$$\sum_j g_{t\tau j} + e_{t\tau} = \hat{d}_{t\tau} - \sum_n \hat{r}_{t\tau n}$$

$$g_{t\tau j} \leq \overline{g}_j$$

Solution approach

1. If we assign a "water value" (Lagrangian) to the hydro generation, the LP is decomposed into $\tau = 1, \ldots, \mathrm{T}$ "economic dispatch" (ED) subproblems with J thermal plants + 1 dummy plant (hydro)
2. The ED subproblems can be solved by inspection (economic loading order) $\Rightarrow$ they can be decomposed into $J + 1$ *generation adequacy* subproblems, where we just compare available capacity with (demand – renewables) (arithmetic operation)
3. Instead of $J + 1$ generation adequacy subproblems, we only need to solve *two:* one where hydro first in loading order (cheapest), another last; the results for all the other intermediate hydro positions are obtained by convex combinations of those two $\Rightarrow$ computational effort is negligible

Pre-calculation of $\beta_t(e_t)$: multiple areas

- In the case of M areas, the generation adequacy check becames a max-flow problem, which is transformed into finding the max of 2^M linear segments (max flow-min cut)
  - GPUs are extremely suitable for this calculation $\Rightarrow$ computational effort is still very small
- Because the number of hydro loading order combinations is now 2^M, the set of constraints $\beta_t \geq \pi_e^p e_t + \delta^p \quad \forall p = 1, \dots, P$ may be large; the relaxation techniques are still very effective, but finding the most violated constraints requires more computational effort
  - GPUs are also very effective in this task

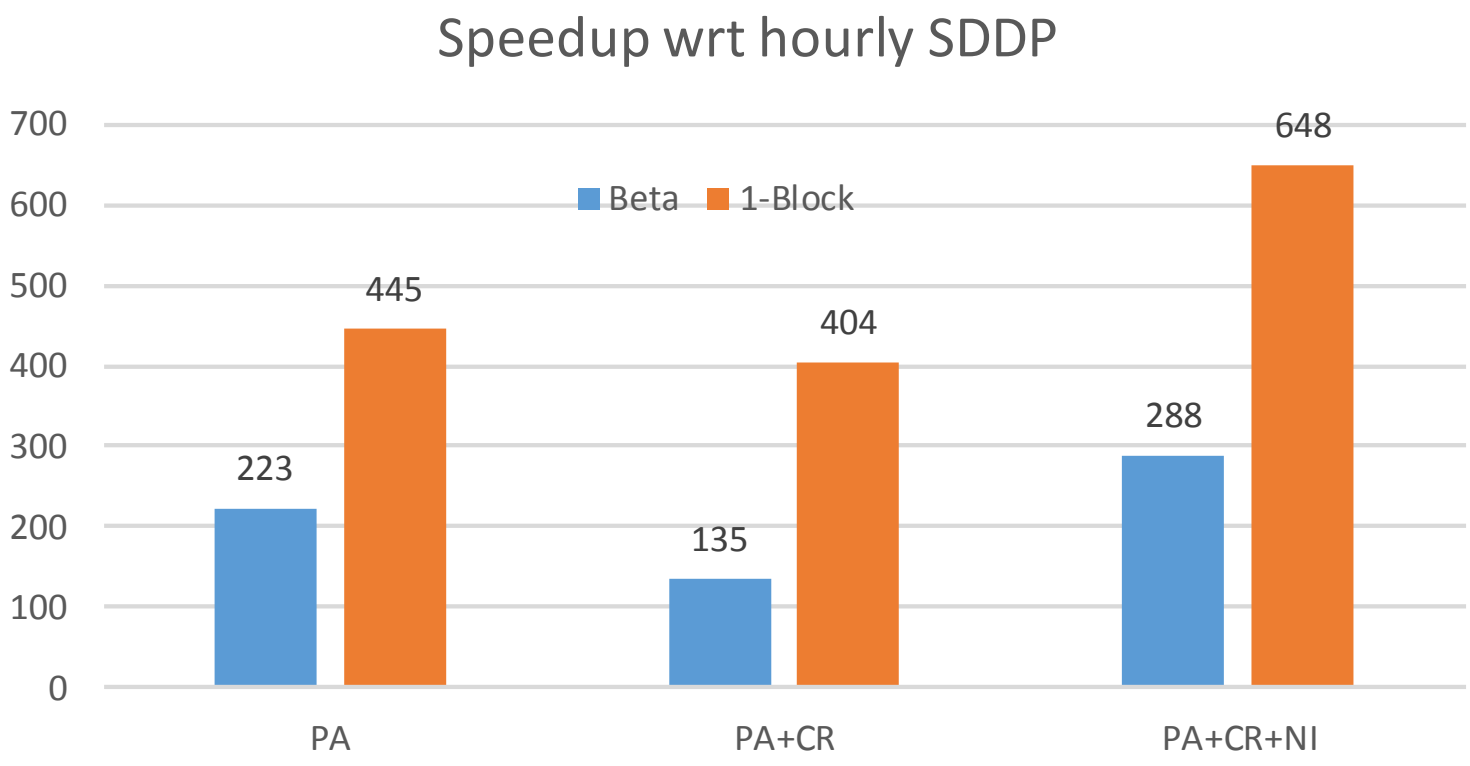
Case study: Central America

Systems: 1. Panama; 2. PA + Costa Rica; 3. PA + CR + Nicaragua

Hourly SDDP run: (average) 730 hours per month

Beta run: SDDP with proposed methodology

1-Block: SDDP with one load block per stage (max theoretical speedup)



Ongoing research

- Representation of storage (e.g. batteries) in the hourly problem: the analytical approximation still applies, but the max flow problem becomes larger due to time coupling; advanced max flow techniques used in machine learning being tested
- New formulation that allows the representation of unit commitment (per block of hours) and an (approximate) transmission network

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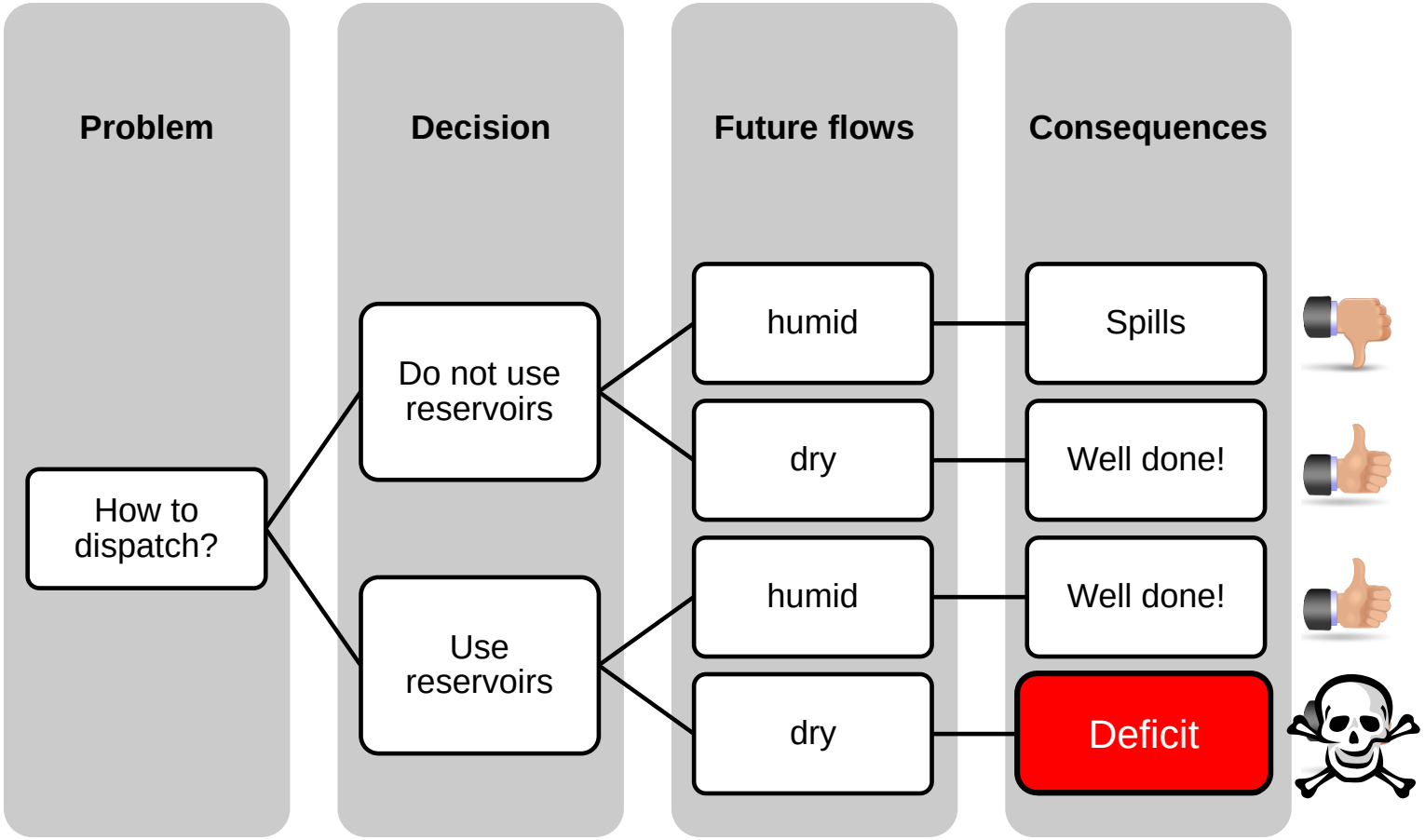
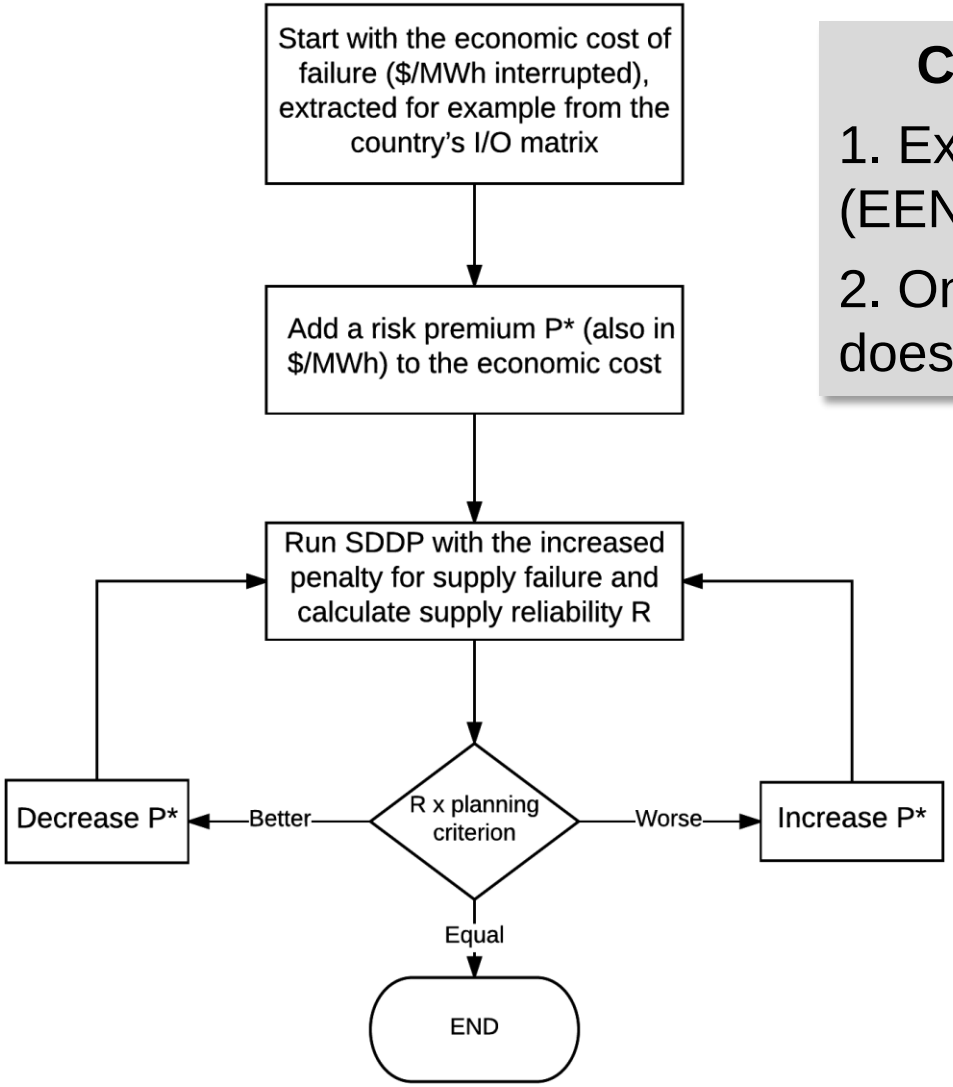
Stochastic optimization with risk aversion



Three approaches to risk aversion

1. Penalize supply failures
   - Economic cost of failure + “risk premium”
2. Ensure feasibility for a set of critical scenarios
   - Hybrid robust/stochastic optimization
3. Give more weight to higher costs in the SDDP recursion
   - Equivalent to skewing the conditioned inflow distribution in SDDP’s backward step

Approach #1: penalize supply failures



Challenge: reliability criterion

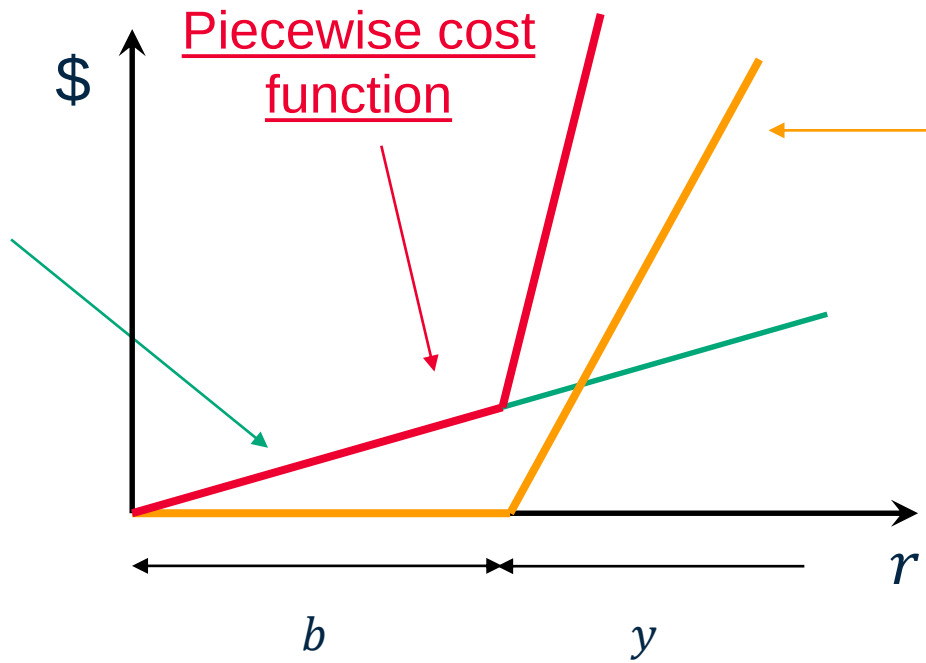
1. Expected energy not supplied (EENS) does not reflect risk of failure
2. On the other hand, risk of failure does not capture *severity*

Proposed criterion: CVaR of EENS

- For example, the expected energy not supplied in the 1% quantile should not exceed 5% of load

Economic cost

slope = δ



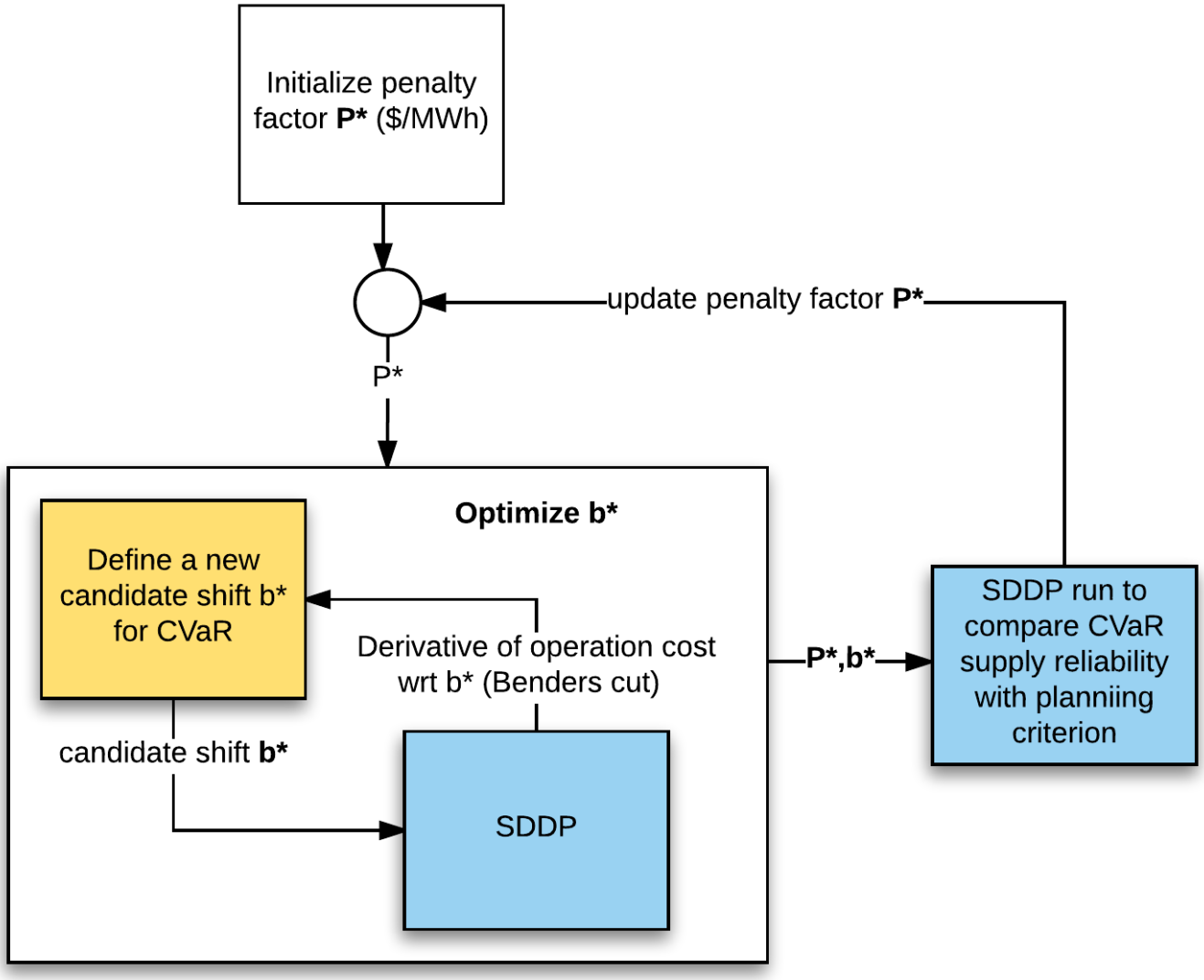
Risk premium function

Associated to CVaR

shift = $\boldsymbol{b}$

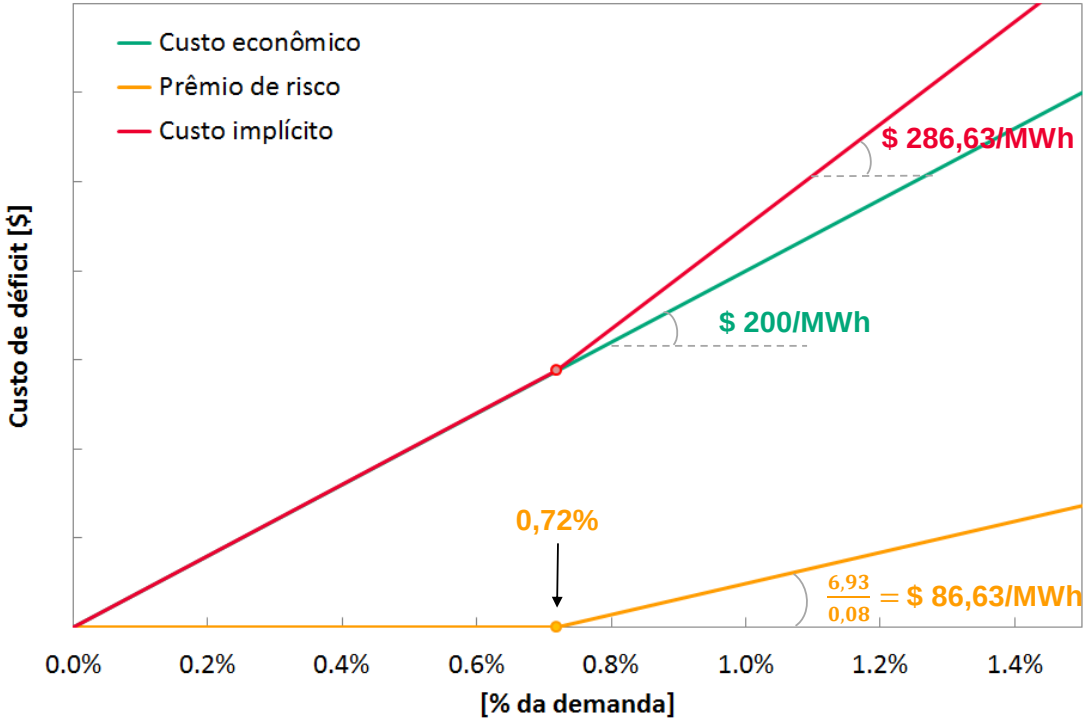
Slope = $p^* = \frac{\mu}{\alpha}$

SDDP with CVaR on supply reliability

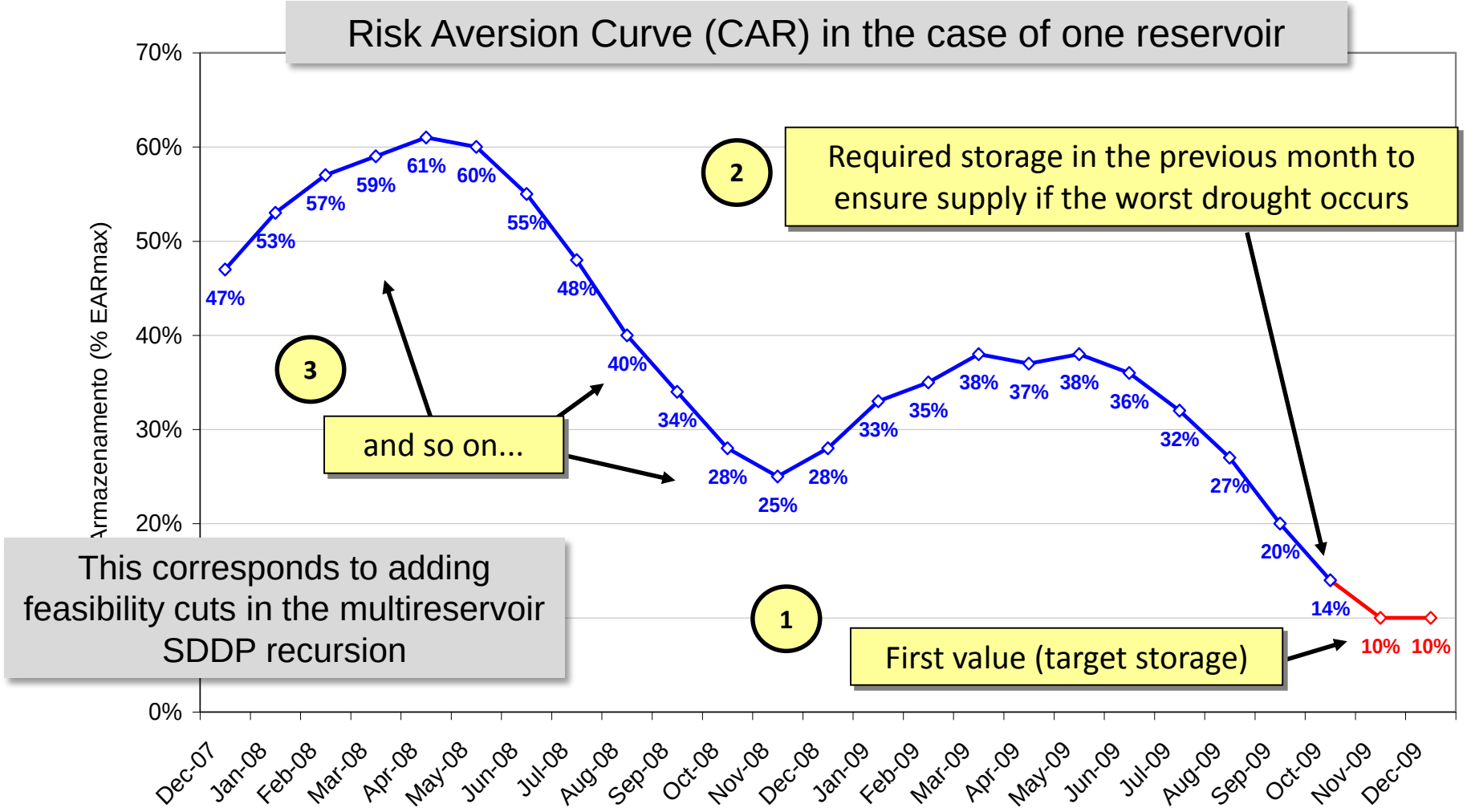


Case study: Costa Rica

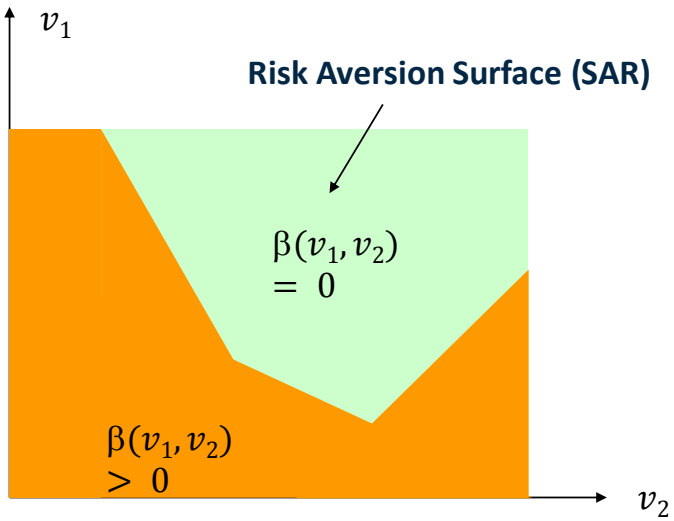
- Economic cost of deficit: 200 $/MWh
- CVaR criterion: EENS @ 5% quantile ≤ 3% load
- SDDP with 125 scenarios forward, 30 branchings backward
- 12 iterations to find optimal premium: ≈ 87 $/MWh



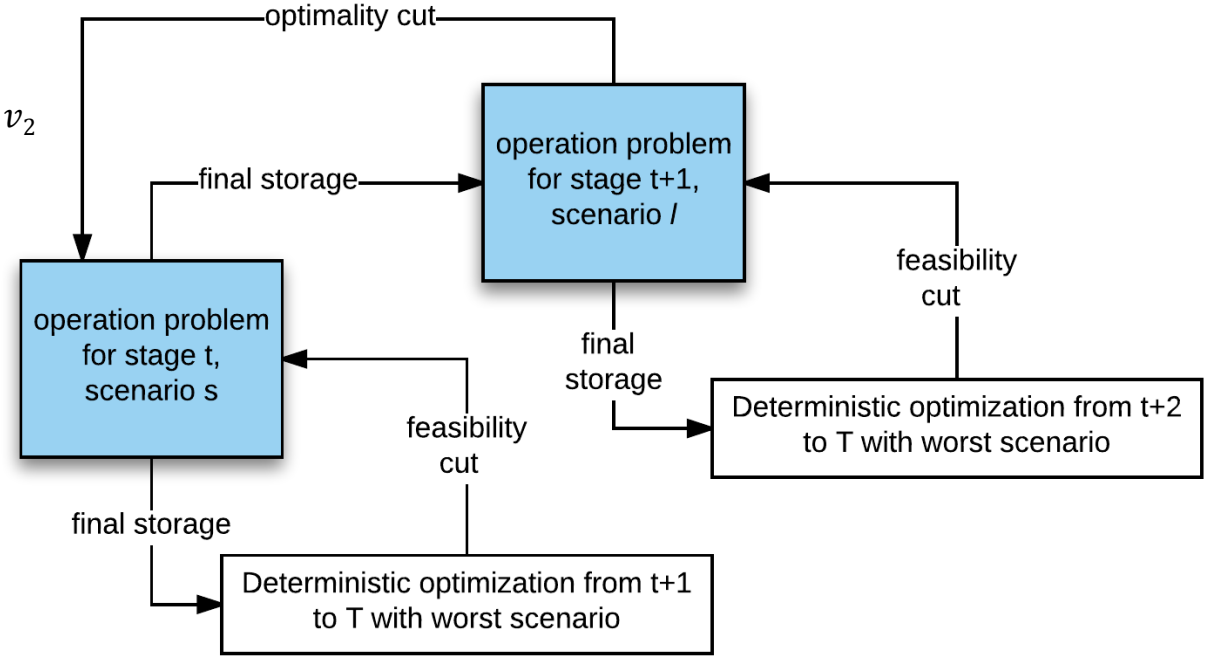
Approach #2: protection against critical scenarios



Risk Aversion Surface (SAR)



CAR and (partially) SAR were used for several years as a risk aversion criterion in Brazil's operation



Approach #3: CVaR on operation cost

- New objective function of the one-stage problem

$$Min\ \lambda E(z) + (1-\lambda)CVaR_q(z)$$

- The CVaR-cost criterion is easy to implement in SDDP, because it is equivalent to changing the weights of the conditioned inflow scenarios in the backward recursion
  - This interpretation also allows a simple and exact calculation of the upper bound in the SDDP algorithm with CVaR, which had been a concern for some time

Comparison of risk aversion approaches

Approach→ Attribute↓	**CVaR-Risk**	**SAR**	**CVaR-cost**
Easy to understand?	Yes	Yes	Medium
Represents risk aversion directly?	Yes	Yes	No
Easy to calibrate?	Medium	Yes	No
Additional computational effort with respect to standard SDDP	High	Medium	Low

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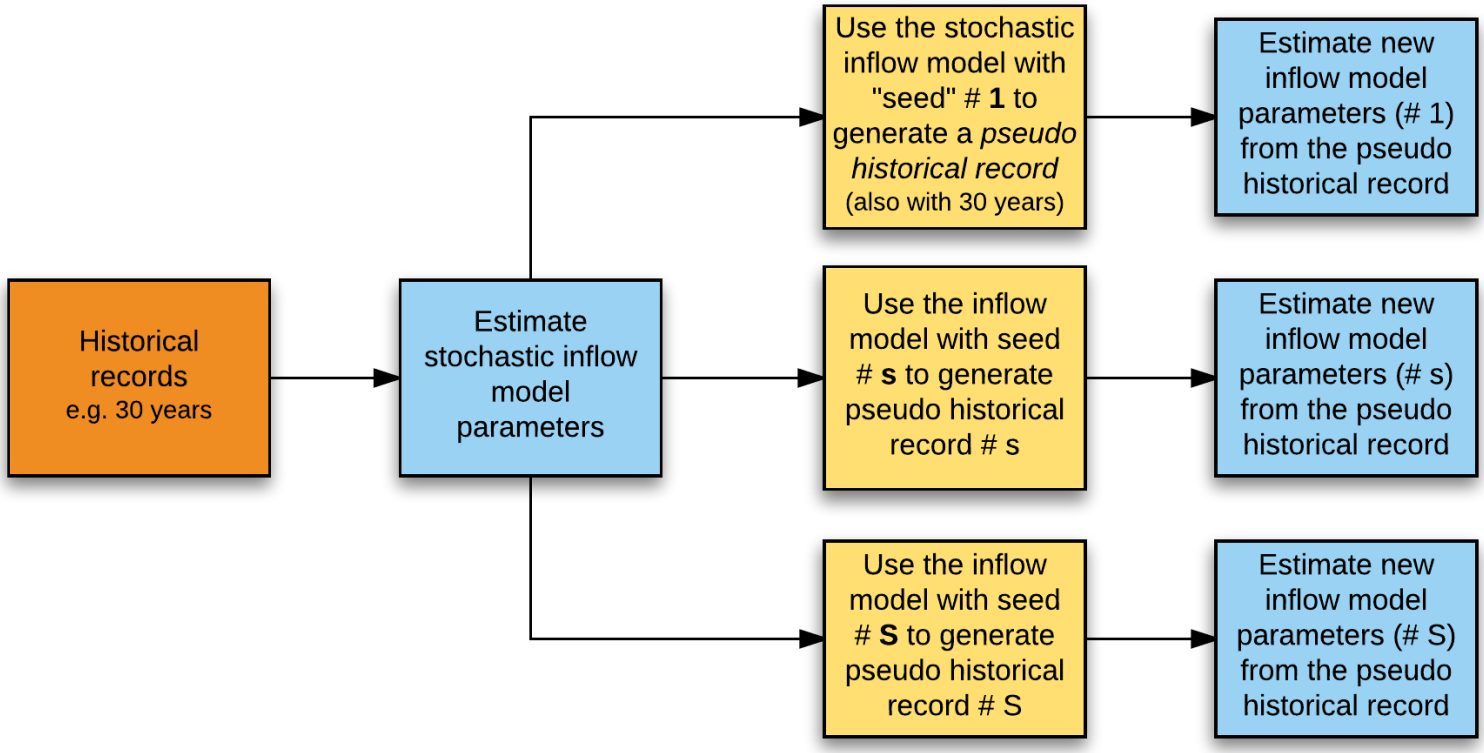
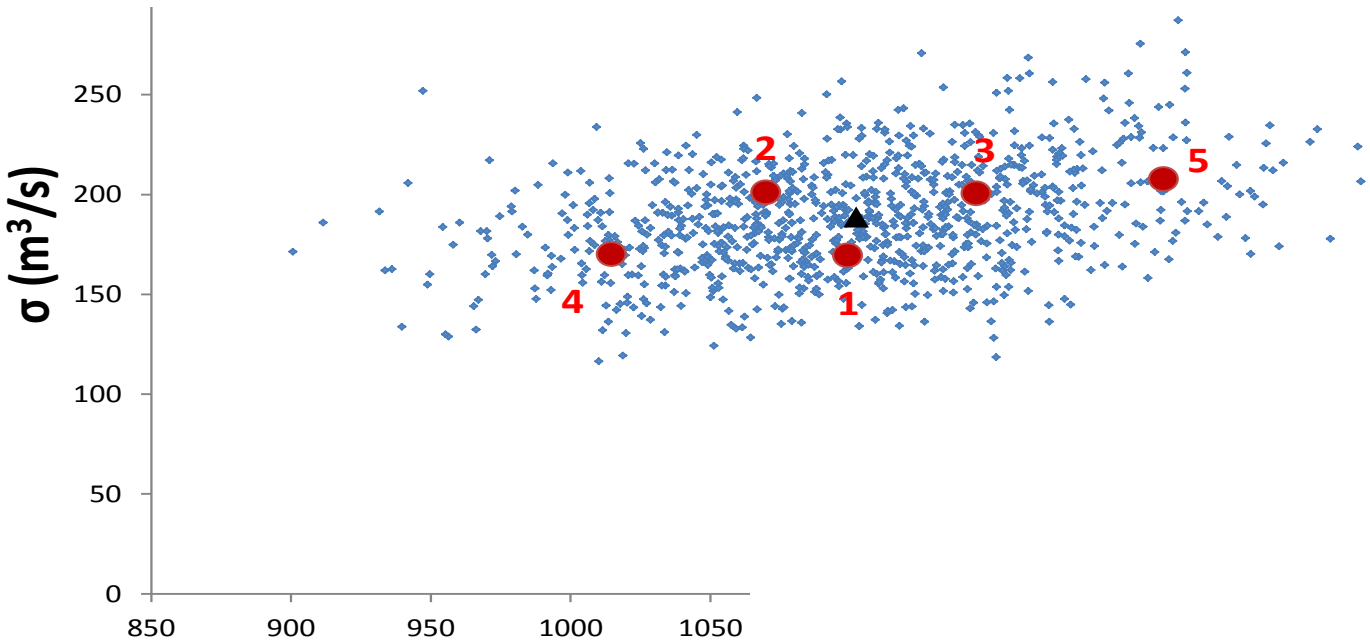
Motivation

- SDDP assumes that the PAR(p) stochastic model parameters (mean, variance etc.) are known, i.e. they are the population values
- However, those parameters are *estimated* from a historical record and there is *uncertainty* around their values $\Rightarrow$ This means that the stochastic optimization results may be “optimistic”
- The concern about parameter uncertainty has increased with the construction of wind generation, because historical records are much smaller

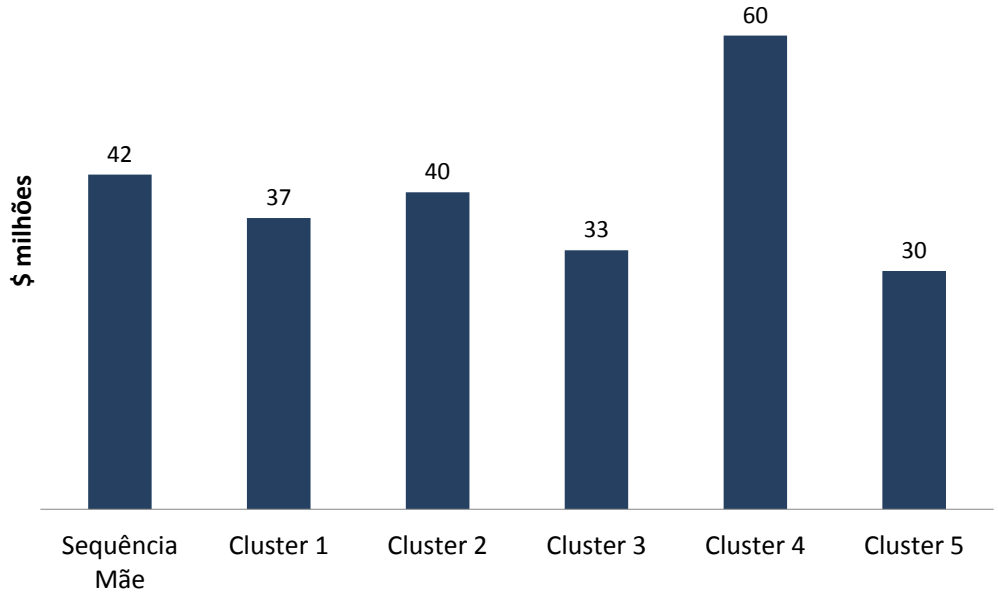
Generation of inflow scenarios with parameter uncertainty



Impact of parameter uncertainty on operation costs



1. Calculate the operating policy with inflow model parameters from the historical record
2. Simulate the system operation with inflows produced by other sets of parameters



Parameter estimation as part of stochastic optimization

1. Minimax criterion
   - Calculate operating policies which are “taylor made” for each set of inflow model parameters $m = 1, \ldots, M$, and simulate system operation with inflow scenarios produced by all the other parameters
   - Use a minimax criterion (or CVaR-cost) on the $M \times M$ operating cost matrix to select the most adequate parameter set
   - The selected set of parameters is “drier” than the estimates from the historical record
2. Represent all the M alternative inflow models as part of the SDDP recursion
   - The implementation is similar to that of CVaR-cost in risk aversion

Other ongoing research

- SDDP-based power planning *strategies*
  - Represents effect of construction times
- Bayesian networks and nonparametric kernel distributions for modeling joint hydro / wind / solar scenarios
- Representation of nonconvexities using Support Vector Regression
- Multistage stochastic Nash Equilibrium
- Composite reliability evaluation using Cross Entropy and MCMC

Conclusions

- Multistage stochastic optimization methods allow the detailed modeling of complex power market features and are computationally feasible even for large systems
- Parallel processing and, more recently, GPUs, are an essential component of the decomposition-based implementations
  - Suitable for representation of functions by hyperplanes in stochastic multistage optimization and reliability evaluation with Monte Carlo
- Promising results from the application of machine learning techniques
  - Max flow techniques for multiscale stochastic scheduling
  - Bayesian networks and kernel-based nonparametric distributions to represent wind and hydro
  - SVR for nonconexities

PSR

THANK YOU