PSR

STOCHASTIC PROGRAMMING MODELS FOR ENERGY PLANNING

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ICSP

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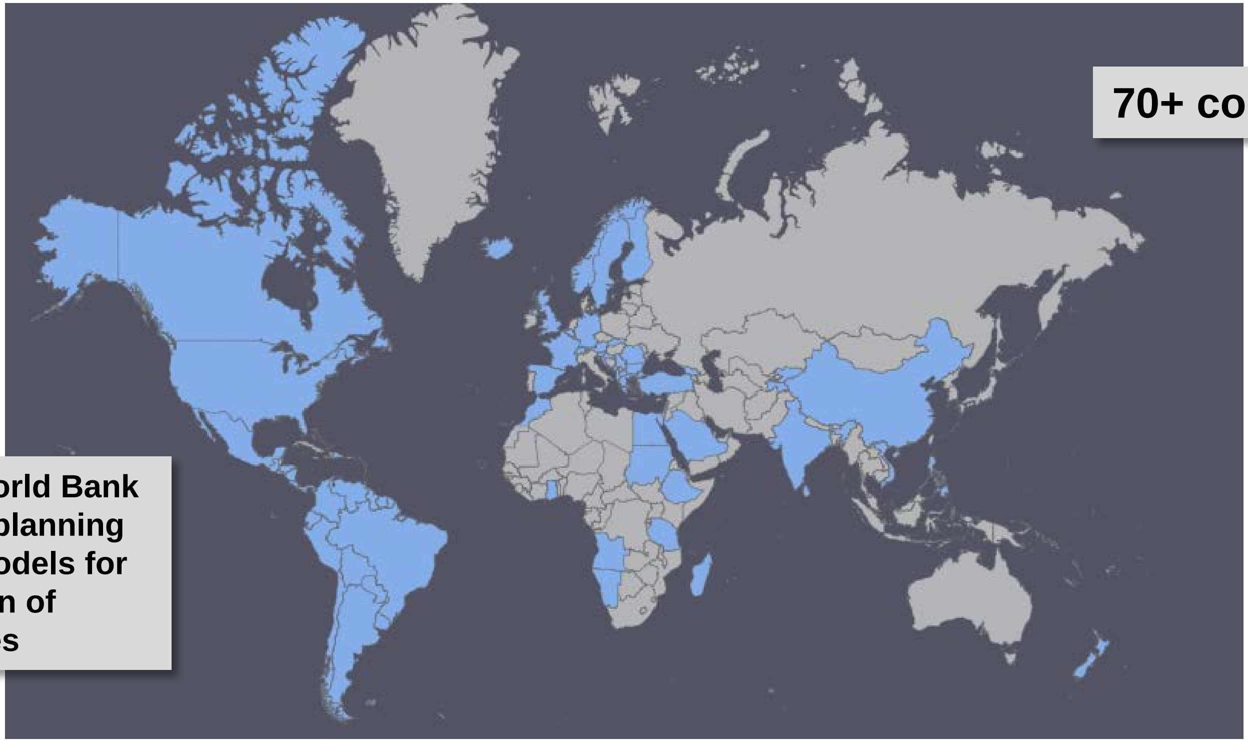
PSR

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

Stochastic models for energy are mainstream



70+ countries

Starting 2015, World Bank uses stochastic planning and operation models for project evaluation of member countries

- **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

Application example

Power Market Trader

Nordic power market outlook

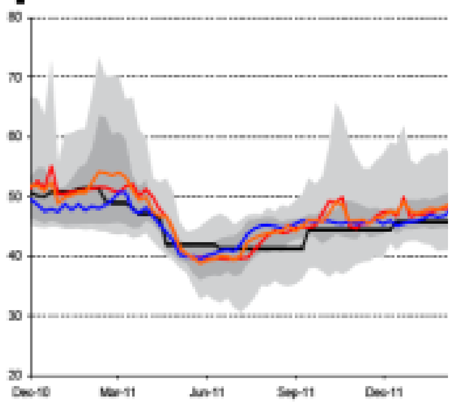
ENERGY

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 -



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.

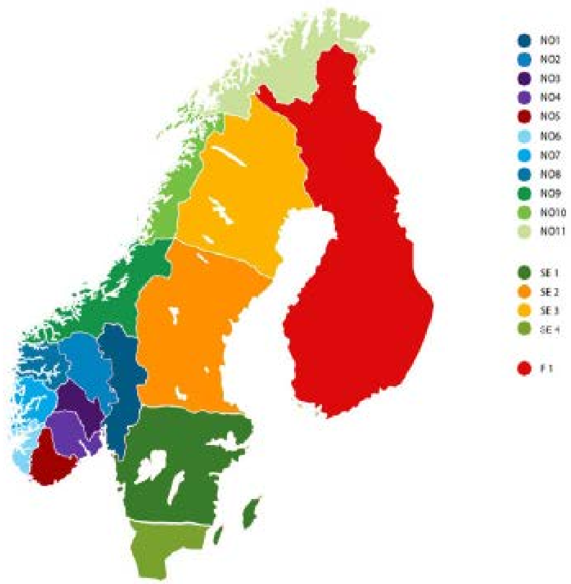


Figure 1: New hydro regions as modeled in the HBV and SDDP models. Notice that the hydro regions for Norway are not identical to the price regions (NO1-5).

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).

Topics

- Current stochastic optimization applications
  - Multistage G&T scheduling – w/ *Ricardo Perez*

  - Integrated G&T expansion planning – *w/ Lucas Okamura*

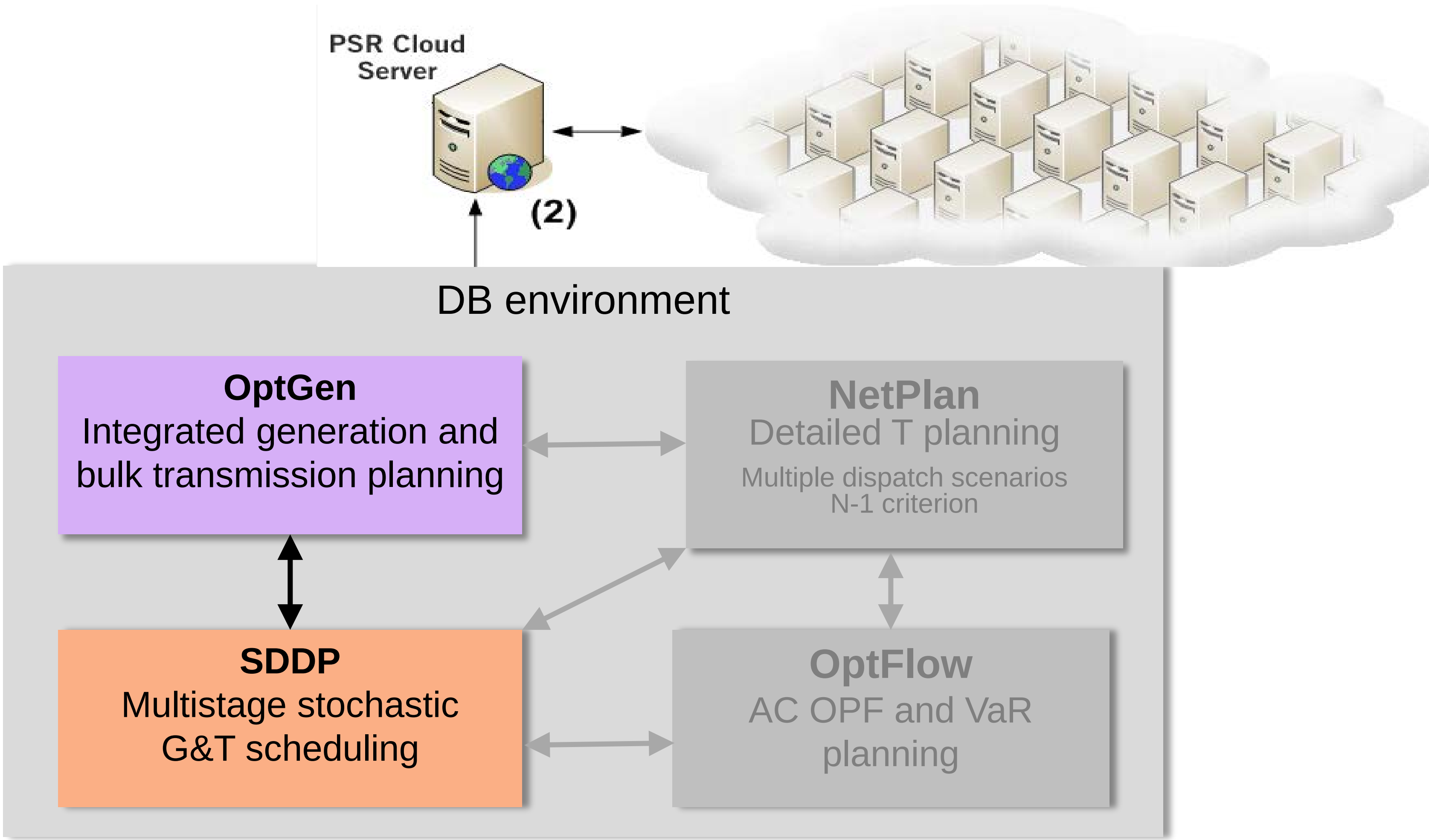
- Recent developments
  - Analytic operating cost function for multiscale dispatch – w/ *Camila Metello*

  - Risk aversion modelling (CVaR and robust approaches) – w/ *L.C.Costa*

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

  - Optimal expansion strategies – *w/ Fernanda Thomé*

Stochastic optimization tools



SDDP: stochastic models

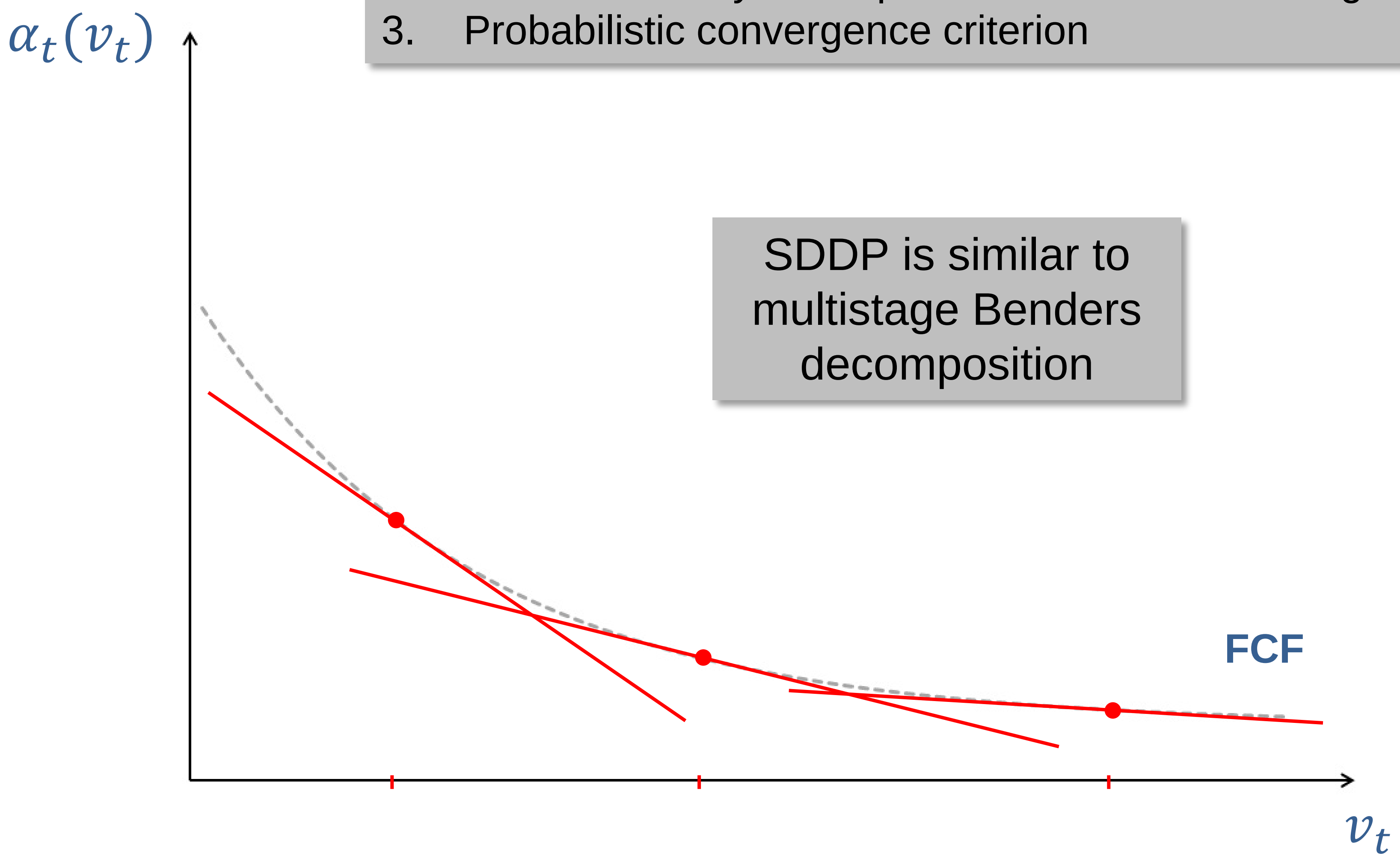
- Hydro inflows and renewable generation (wind, solar, biomass etc.)
  - Multivariate stochastic model (PAR(p))
    - Inflows: macroclimatic events (El Niño), snowmelt and others
    - Spatial correlation of wind, solar and hydro
    - External renewable models can be used to produce scenarios
- Uncertainty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

SDDP: representation of energy systems

- 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.

Stochastic Dual DP

1. Piecewise linear approximation of FCF
2. Simulation of system operation to find "interesting" states
3. Probabilistic convergence criterion



SDDP algorithm

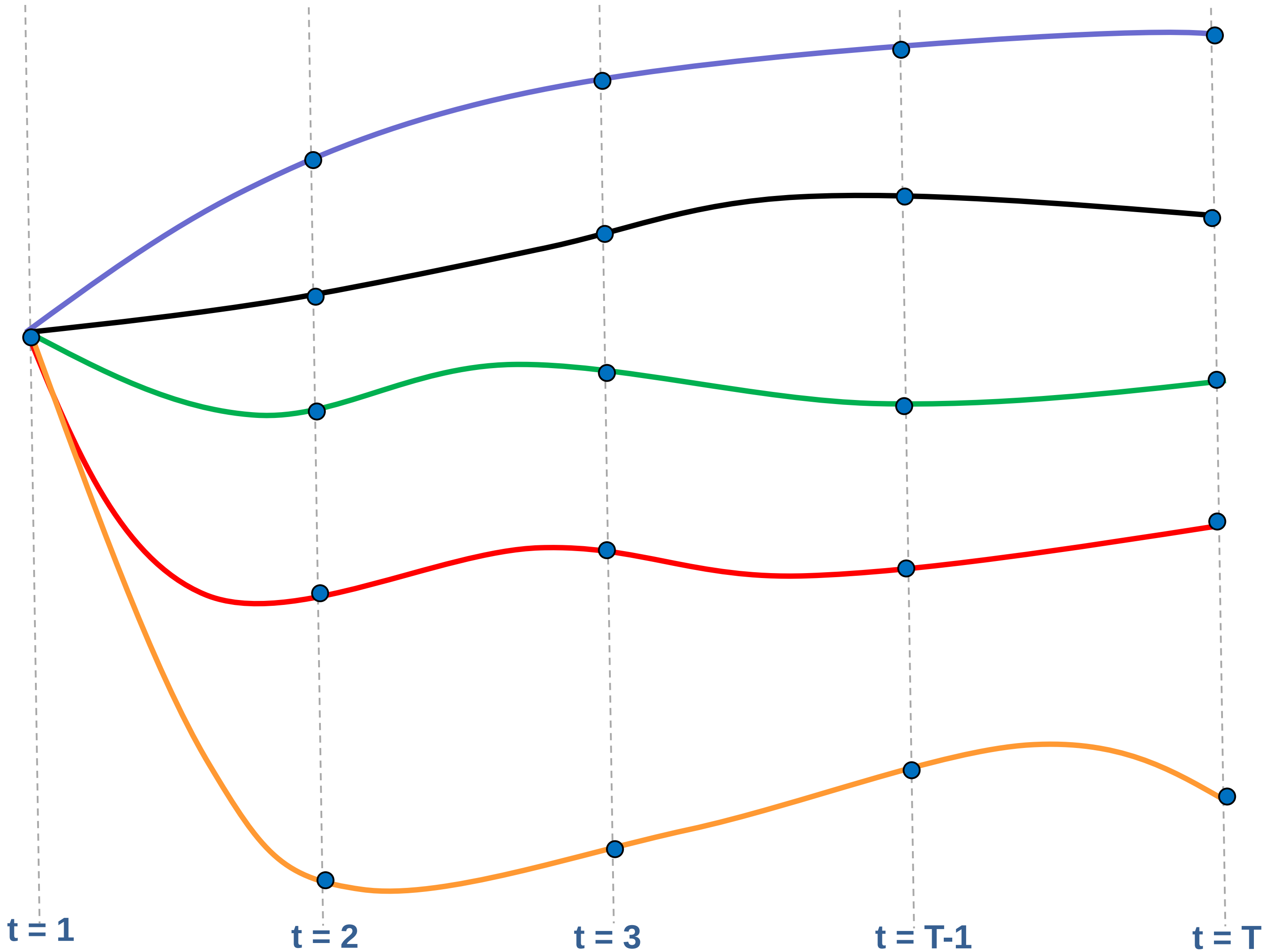
Iterative procedure

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)

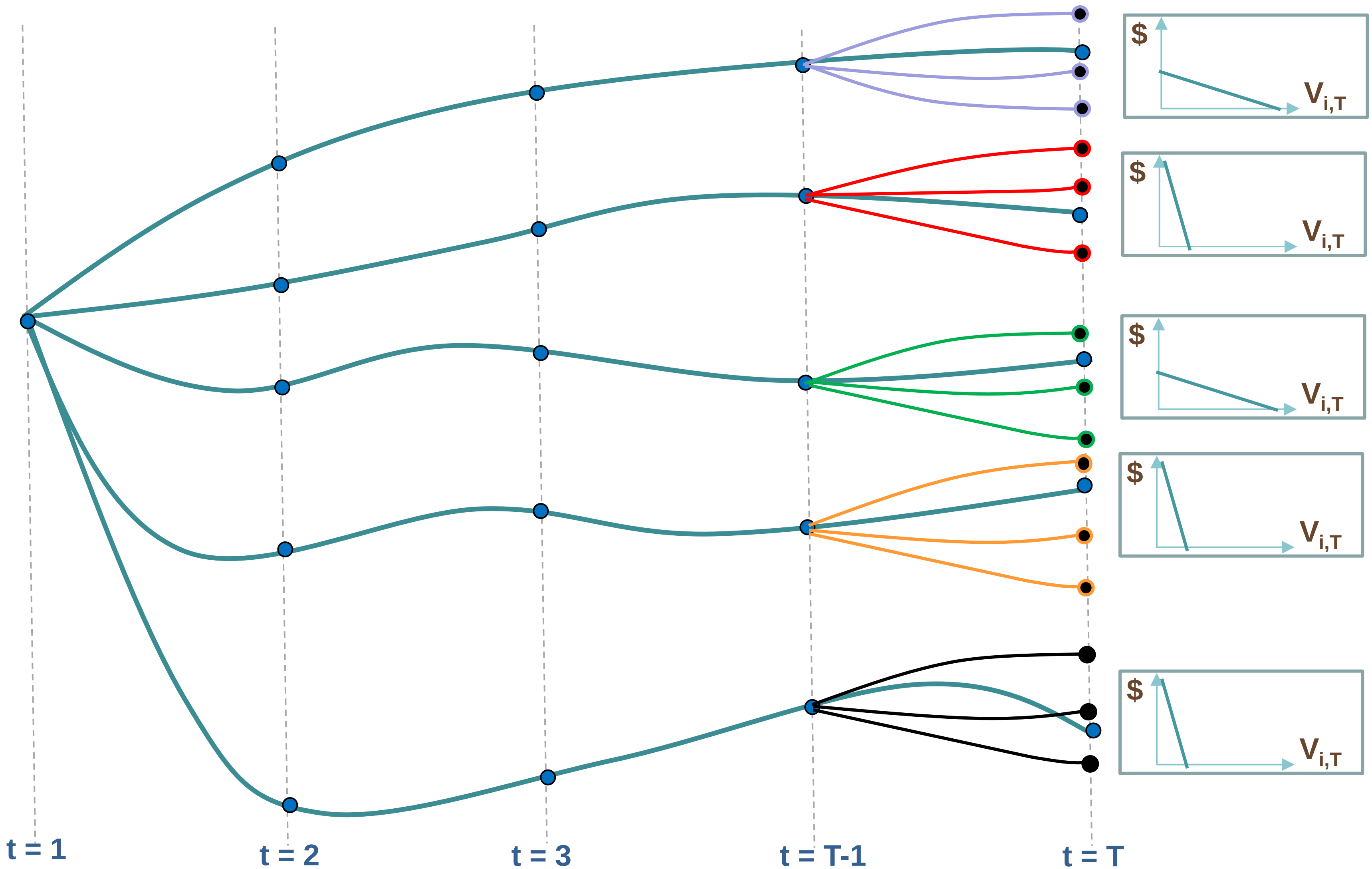
Distributed processing

- 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 termal plants (gas, coal, oil and), 8 GW wind, 5 GW biomass, 1 GW 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

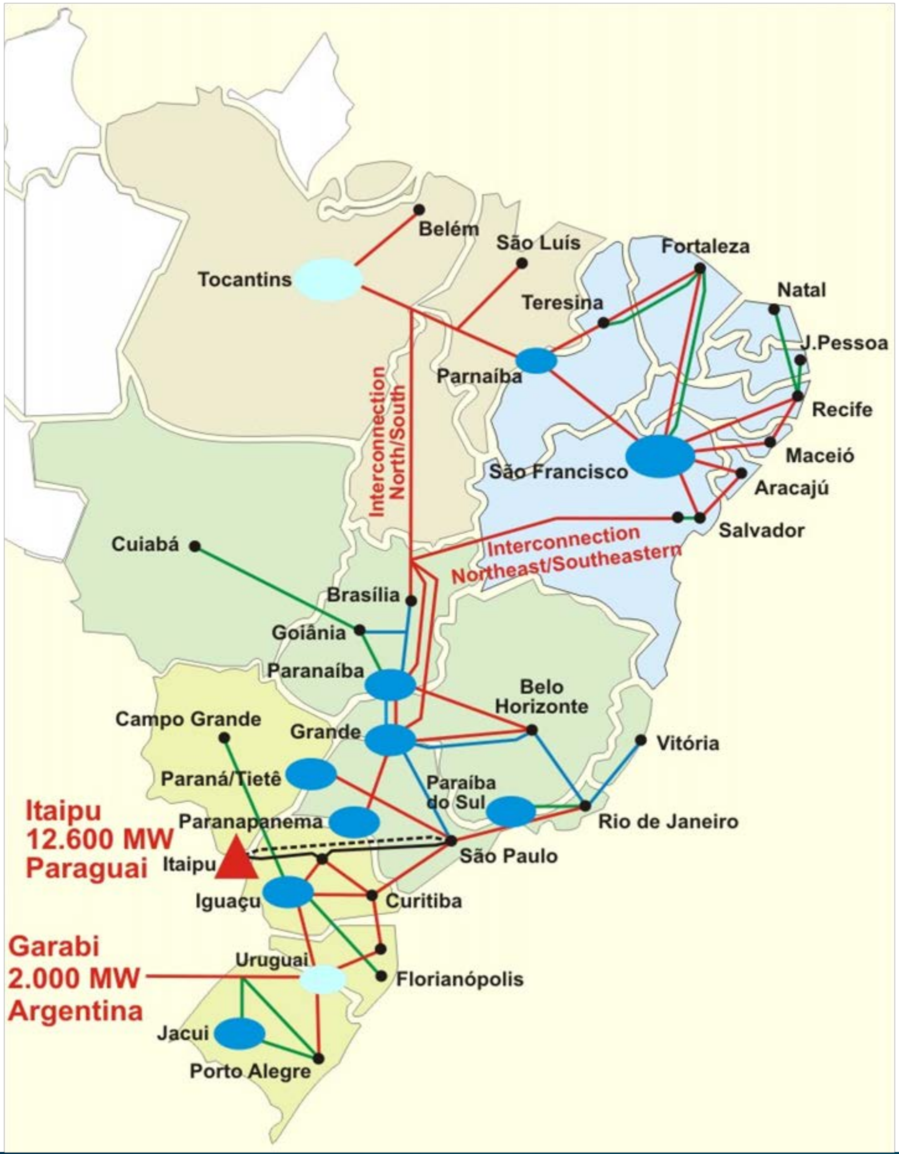
Forward scenarios: 1,200

Backward branching: 30

Number of SDDP iterations: 10

43 million LPs

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



Overview

- Current stochastic optimization applications
  - Multistage G&T scheduling
  - Integrated G&T expansion planning
- Recent developments
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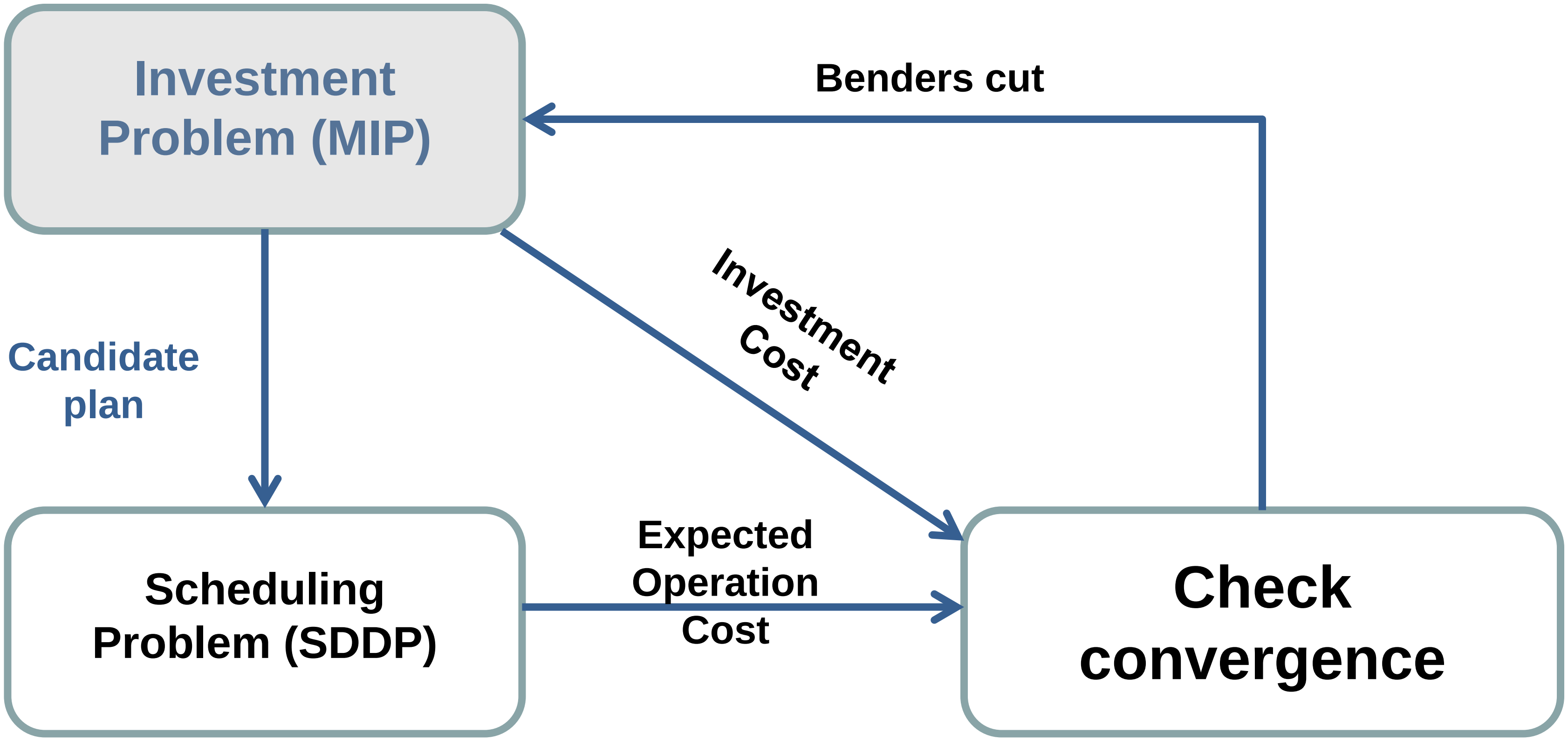
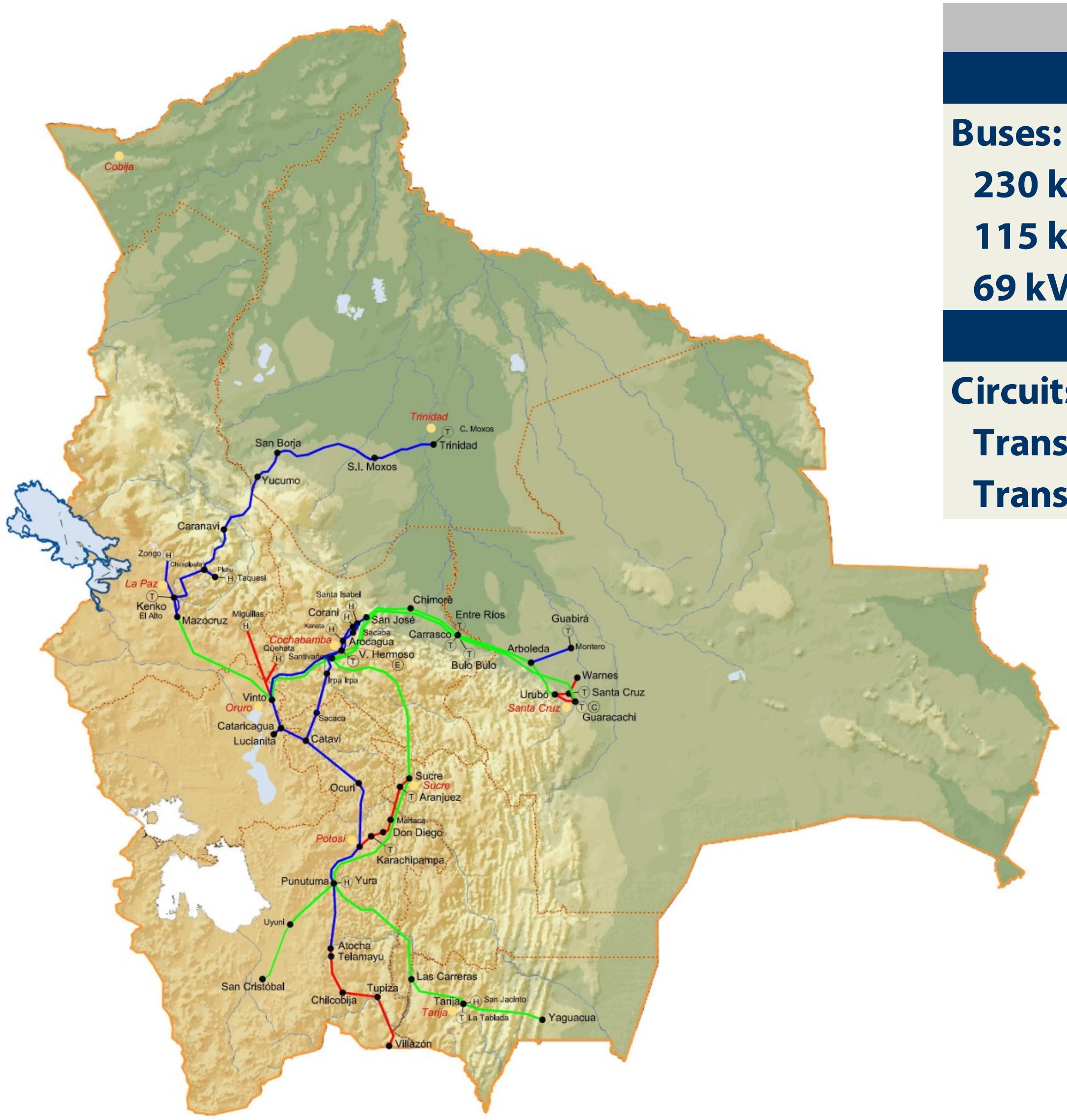
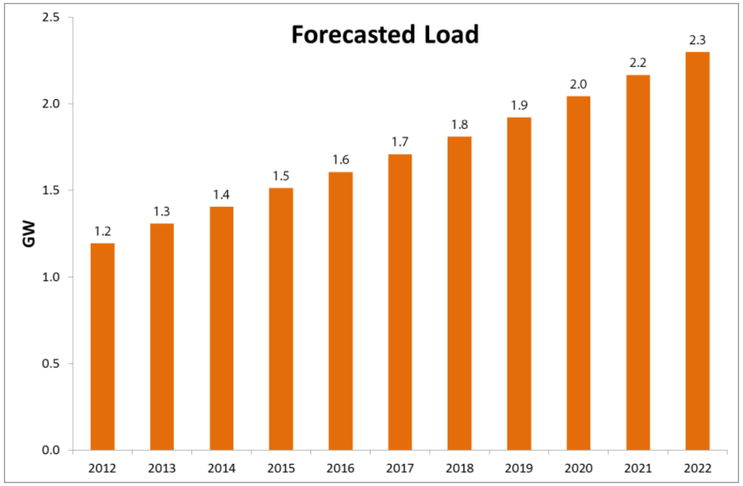
Optgen: generation & transmission planning



Example: Bolivia



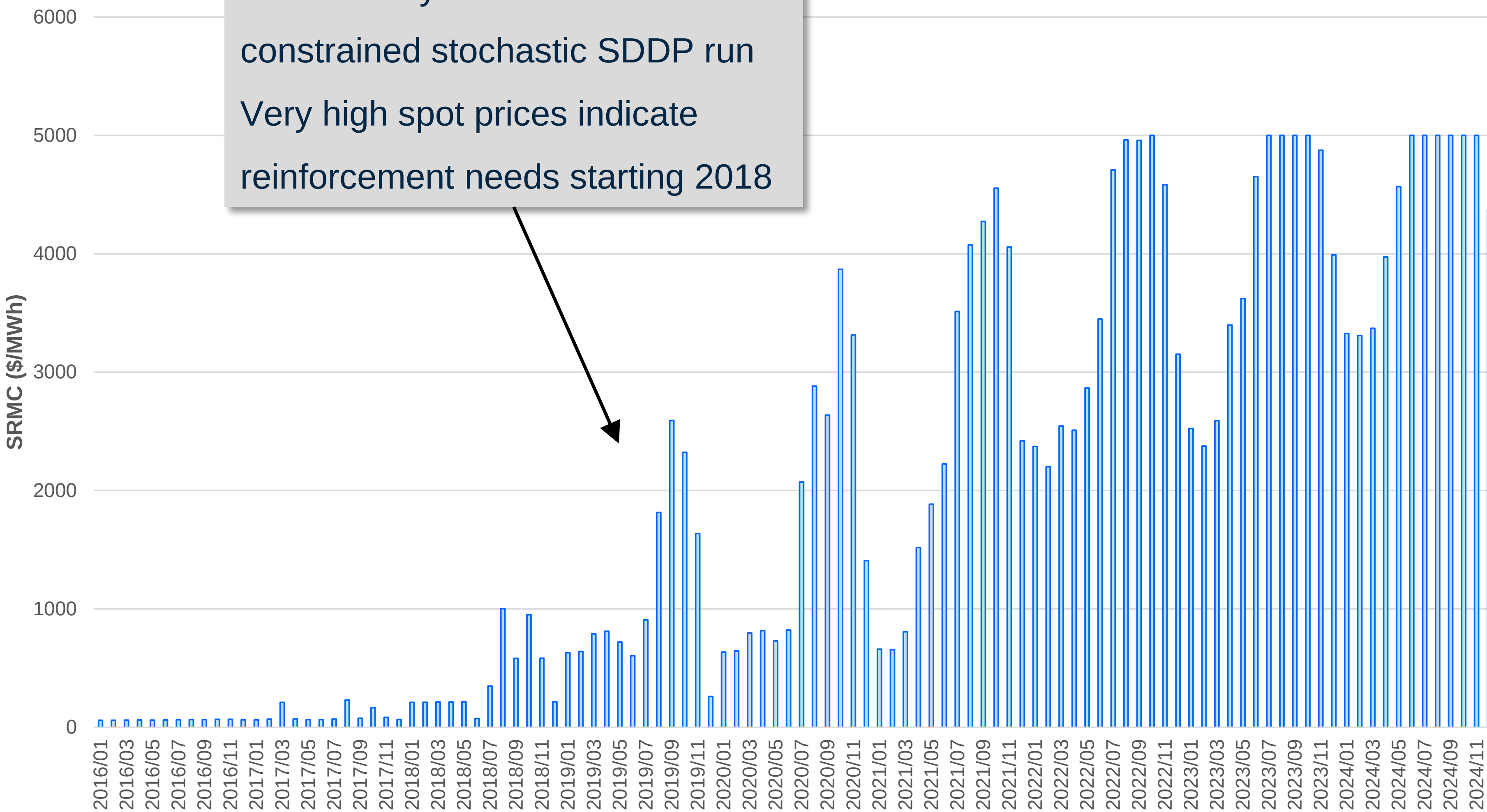
Transmission System	
Buses:	**141**
230 kV	**29**
115 kV	**72**
69 kV	**40**
Circuits	**127**
Transmission lines:	**100**
Transformes:	**27**



System spot prices – no reinforcements

Produced by a transmission constrained stochastic SDDP run

Very high spot prices indicate reinforcement needs starting 2018



Generation & transmission expansion plan

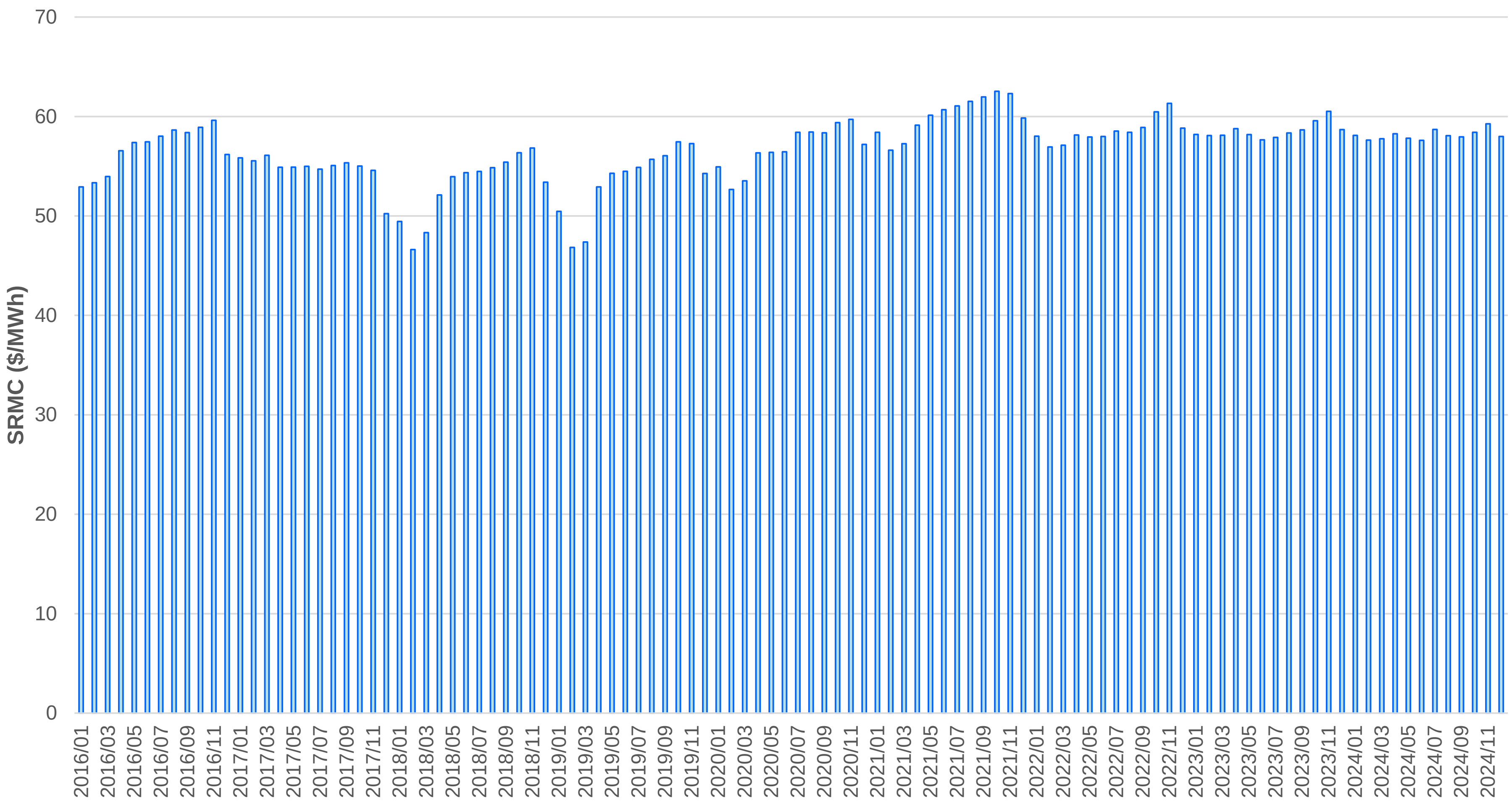
Study parameters

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

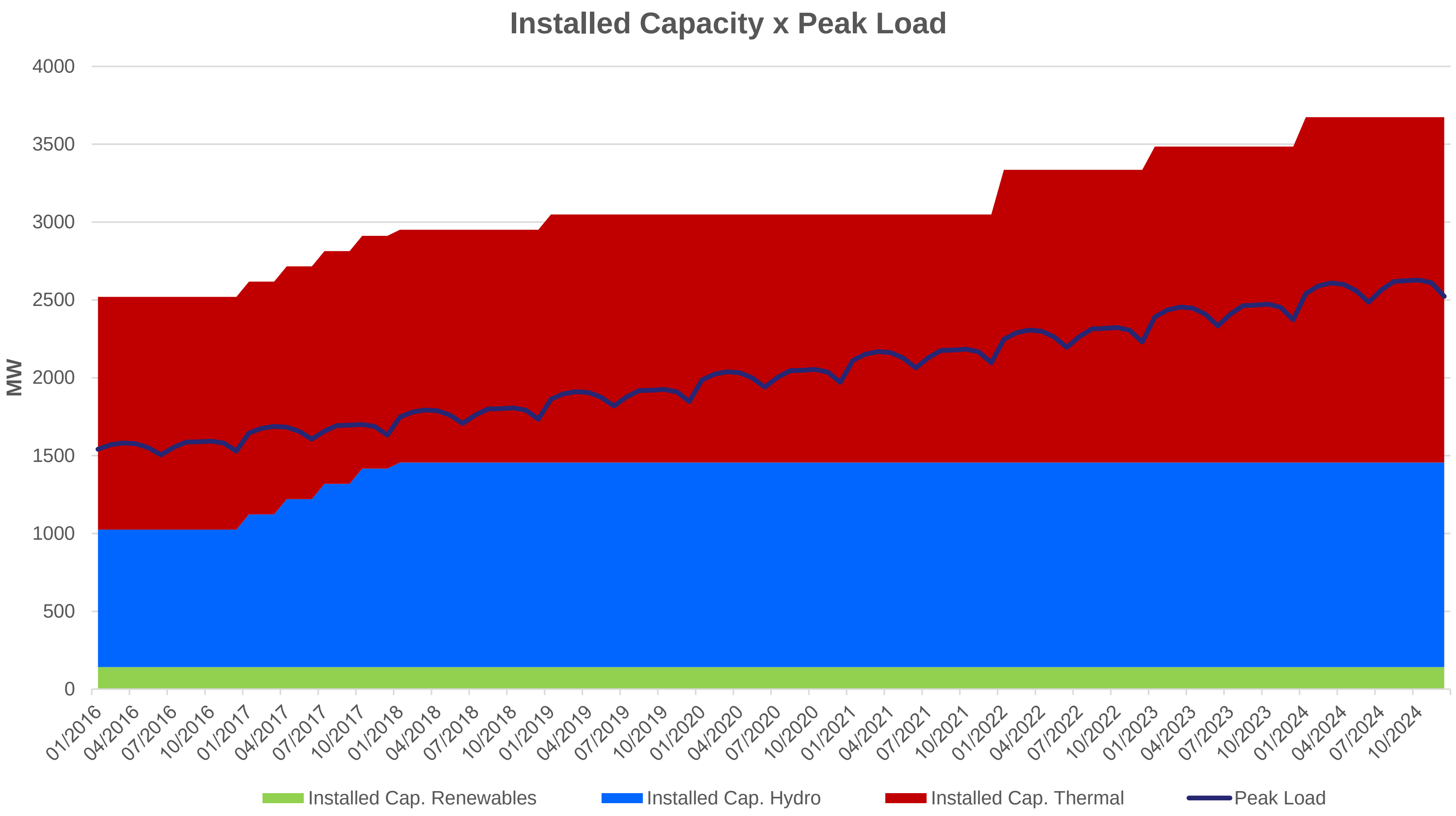
Computational results

- 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

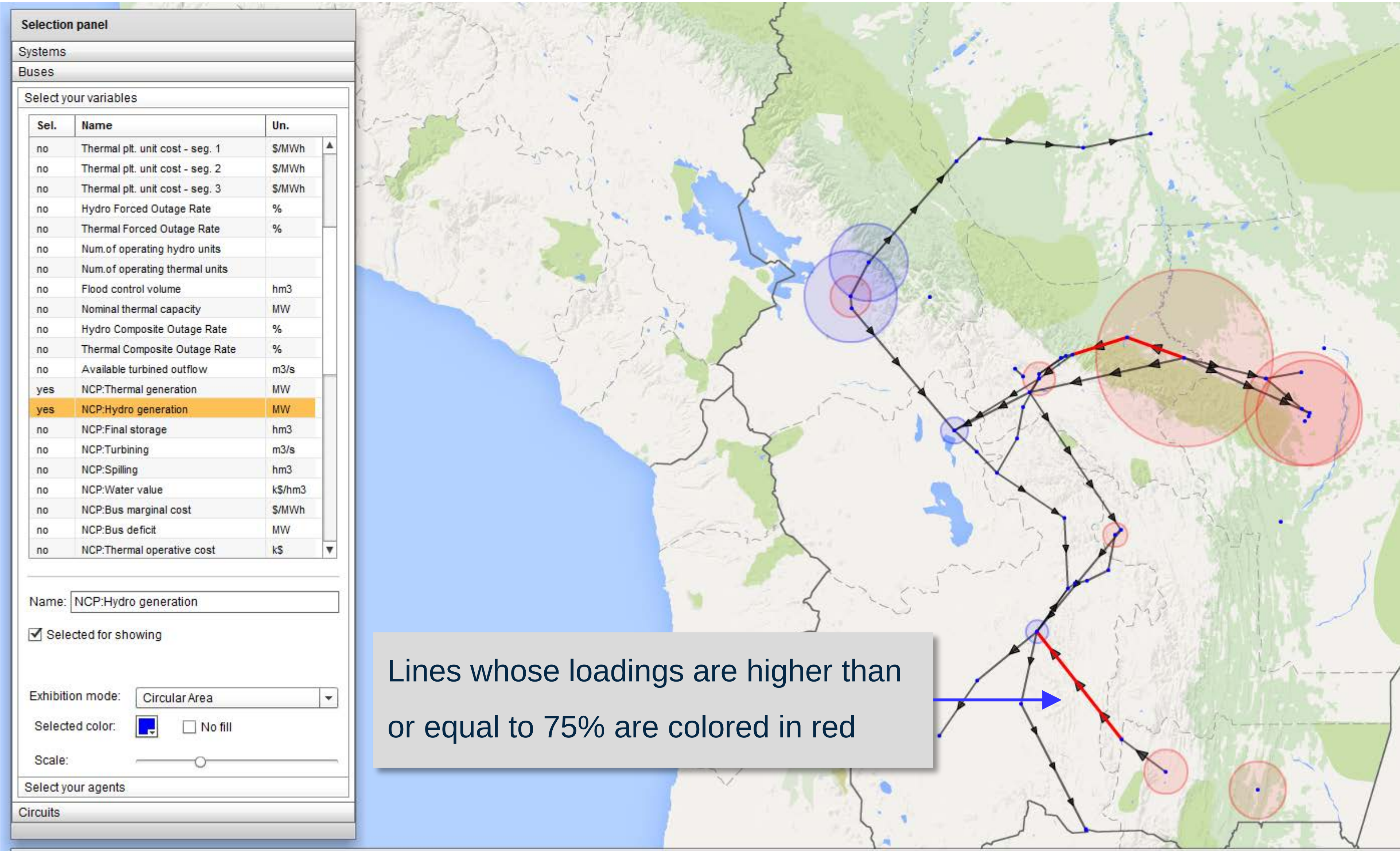
Spot prices - after optimal expansion



Optimal generation expansion plan



Transmission reinforcements



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

In summary…

- 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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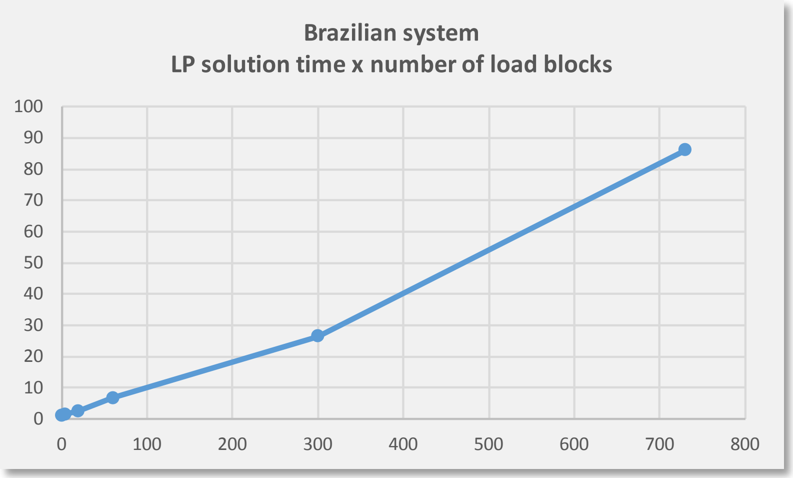
Motivation

- 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



Standard one-stage operation problem (simplified)

- Objective: Min immediate cost + future cost

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

- Storage balance

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

- Power balance

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

- Future cost function (FCF)

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

Relaxation schemes for FCF constraints

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

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

> - 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

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

$$\sum_\tau e_{t\tau} = e_t \leftarrow \text{coupling constraint}$$

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

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

Solution approach

1. If we assign a "water value" (Lagrangian) to the hydro generation, the LP is decomposed into $\tau = 1, \dots, \mathcal{T}$ hourly subproblems with J thermal plants + 1 dummy plant (hydro)
2. The 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 with the hydro first (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 supply adequacy problem becomes a max-flow, which is solved by max flow-min cut
  - GPUs are suitable for Max $\{2^M$ linear constraints$\}$ $\Rightarrow$ computational effort is still small

Watch Camila's presentation
Speedups of two orders of magnitude!

- 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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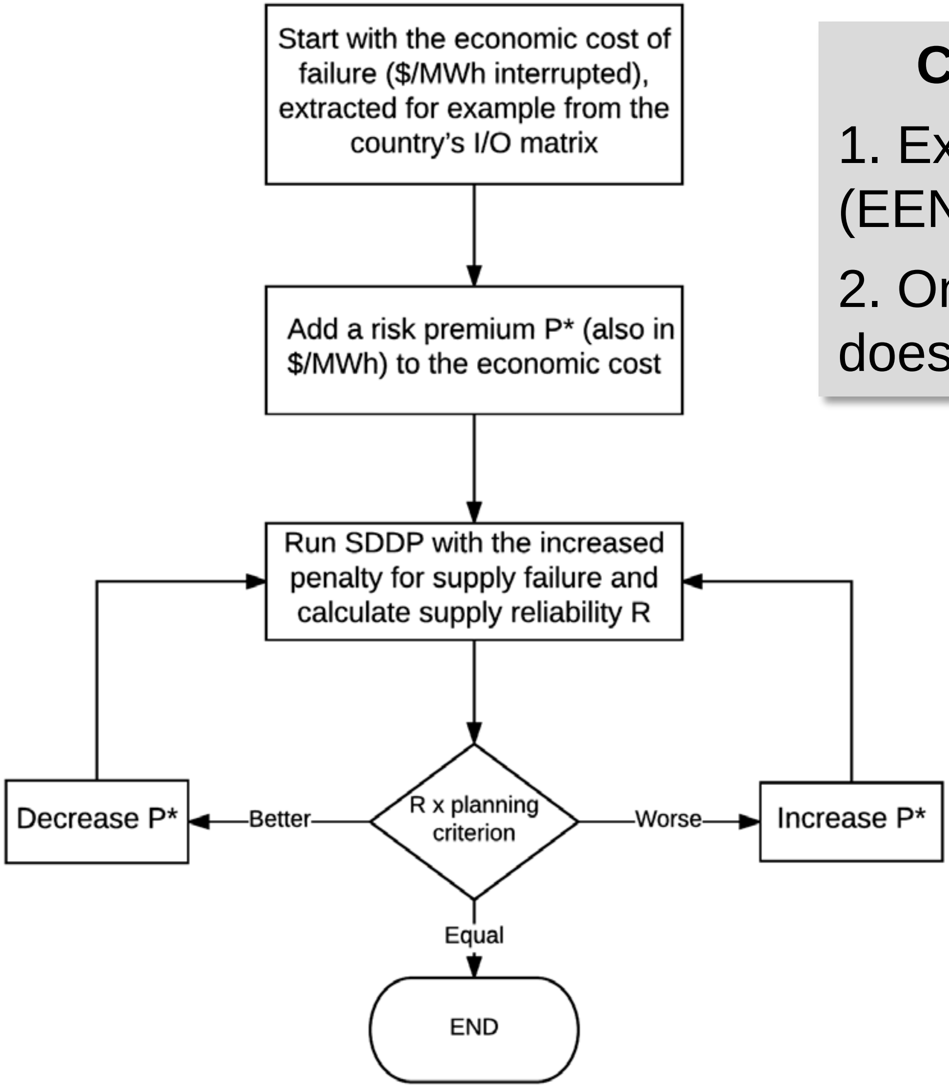
Three approaches to risk aversion

1. Penalize supply failures
   - Economic cost of failure + “risk premium”
2. Ensure feasibility for a set of critical scenarios
   - Hybrid robust/stochastic optimization
3. CVaR on costs (Shapiro and others)
   - 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



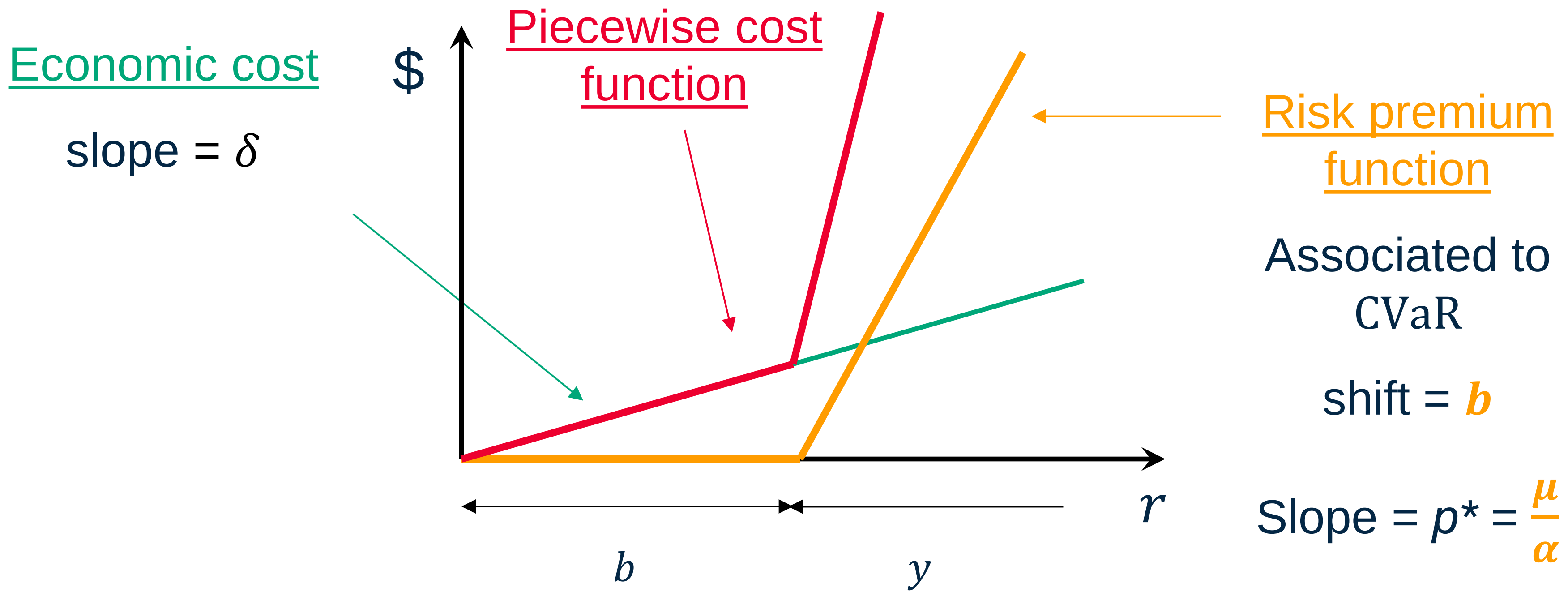
Challenge: reliability criterion

1. Expected energy not supplied (EENS) does not reflect risk of failure

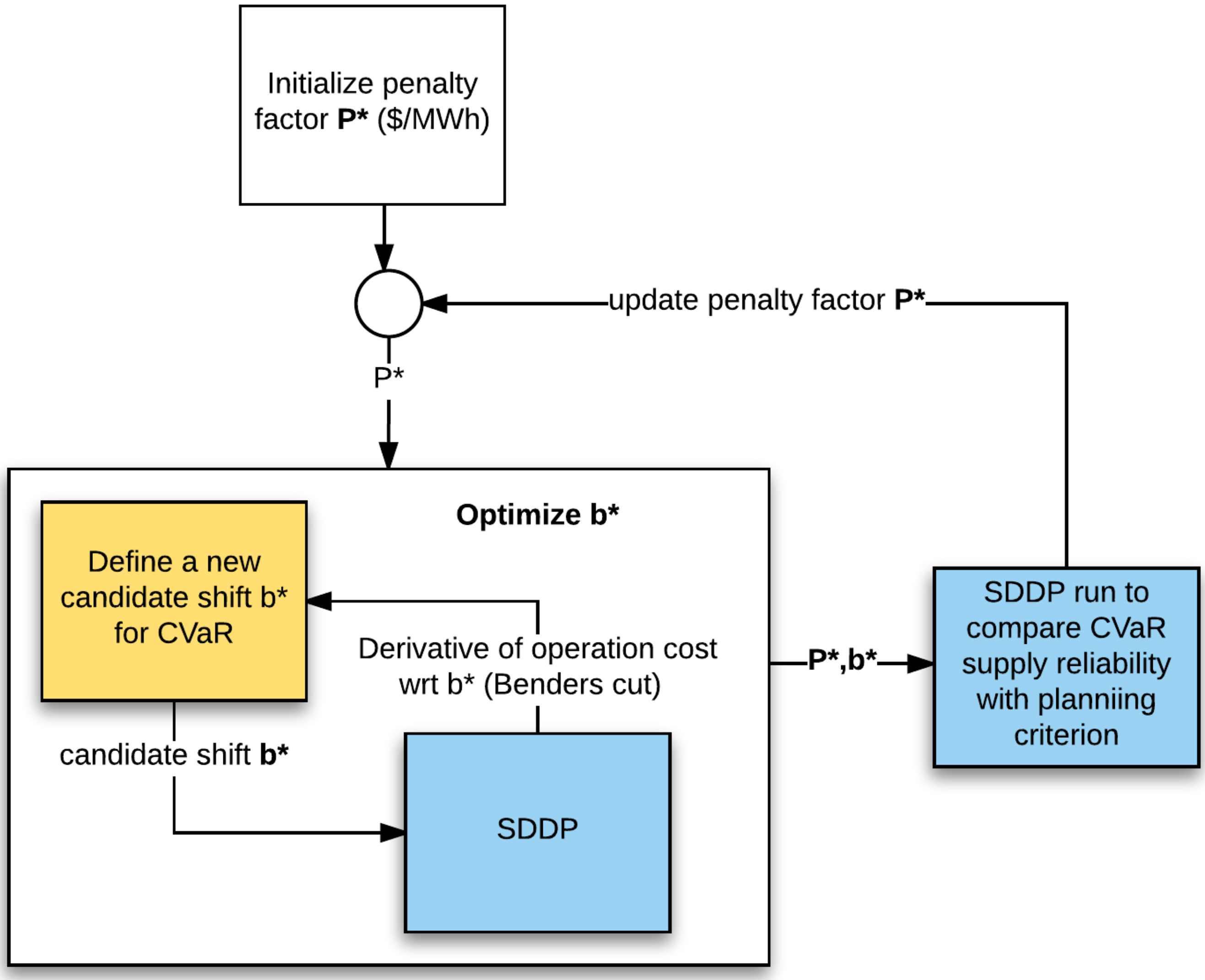
2. On the other hand, risk of failure does not capture *severity*

Proposed criterion: CVaR of EENS

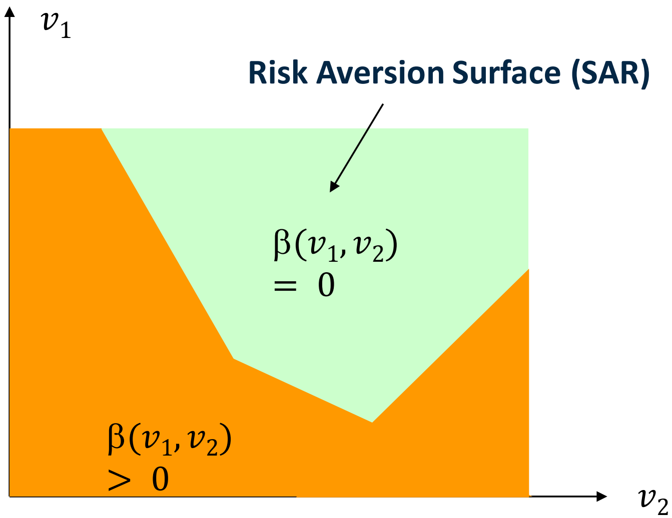
- For example, the expected energy not supplied in the 1% quantile should not exceed 5% of load



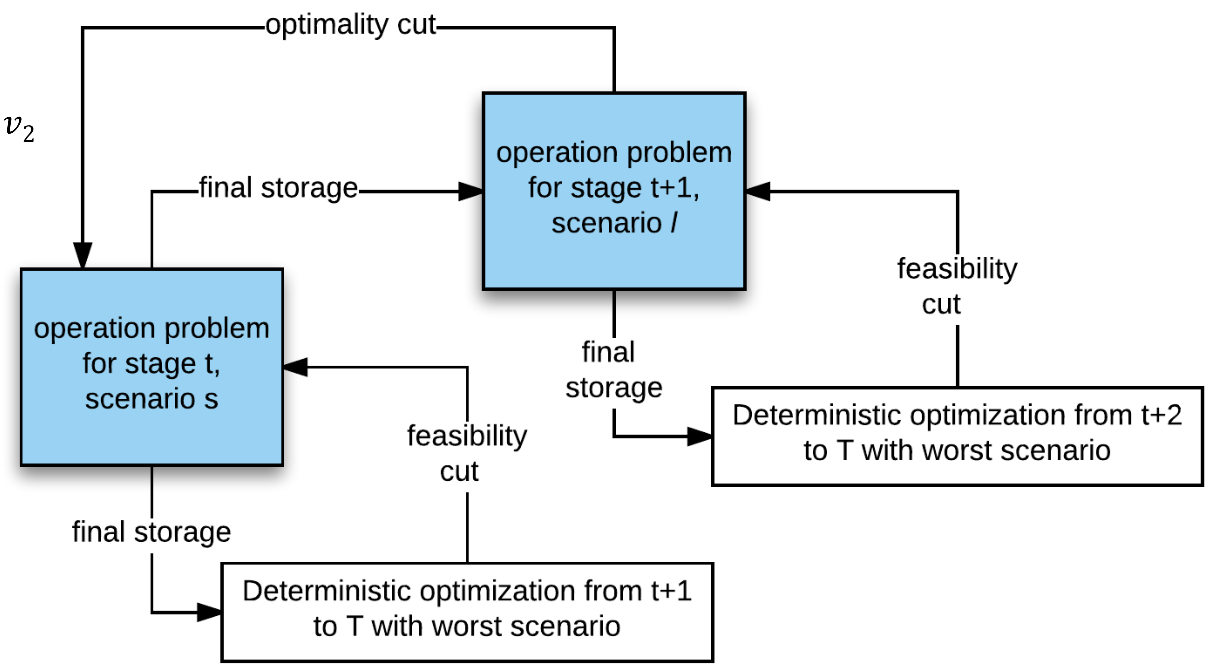
SDDP with CVaR on supply reliability



Approach #2: Risk Aversion Surface (SAR)



A version of SAR was used for several years to represent risk aversion 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	Sort of…
Represents reliability targets directly?	Yes	Yes	No
Easy to calibrate?	Medium	Yes	Medium
Additional computational effort with respect to standard SDDP	High	Medium	Low

Watch Luiz Carlo's presentation to see the real-life case studies!

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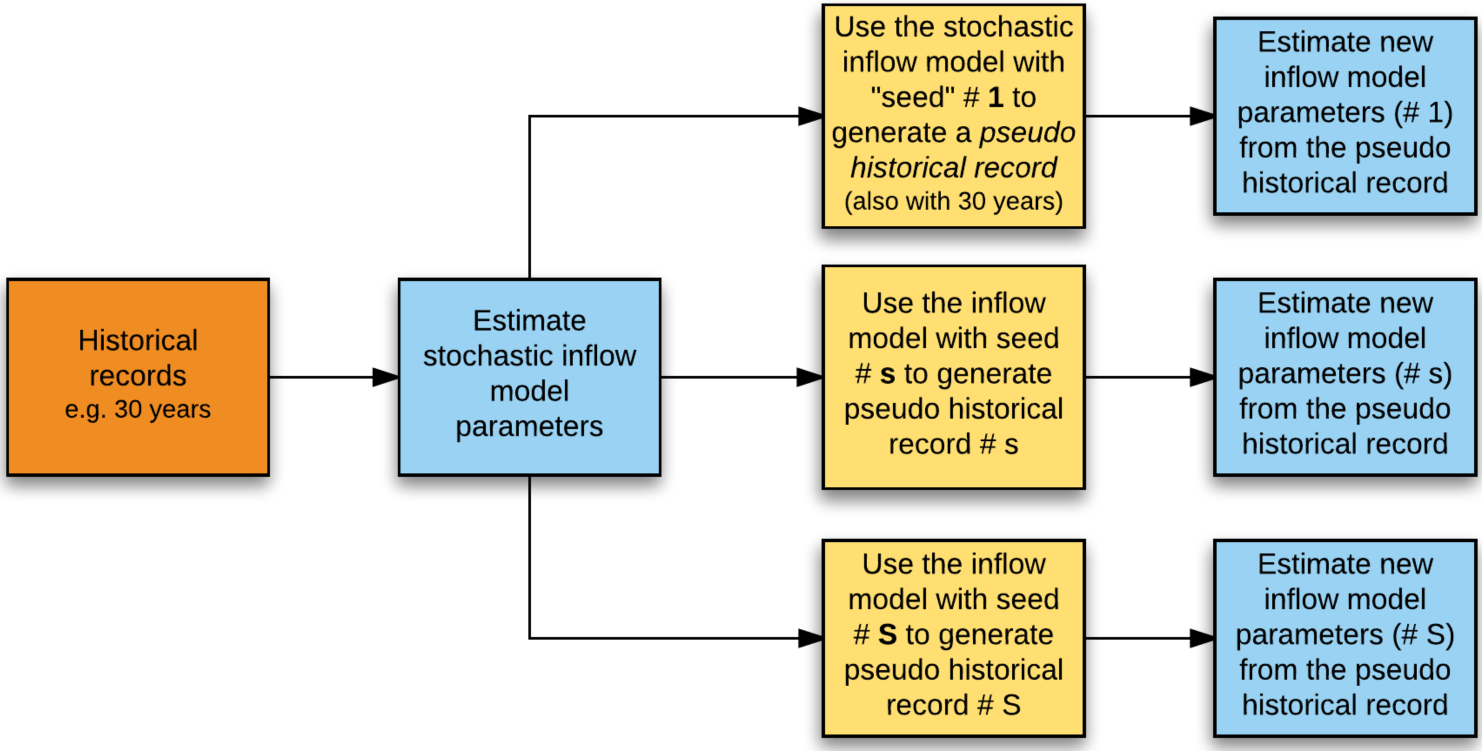
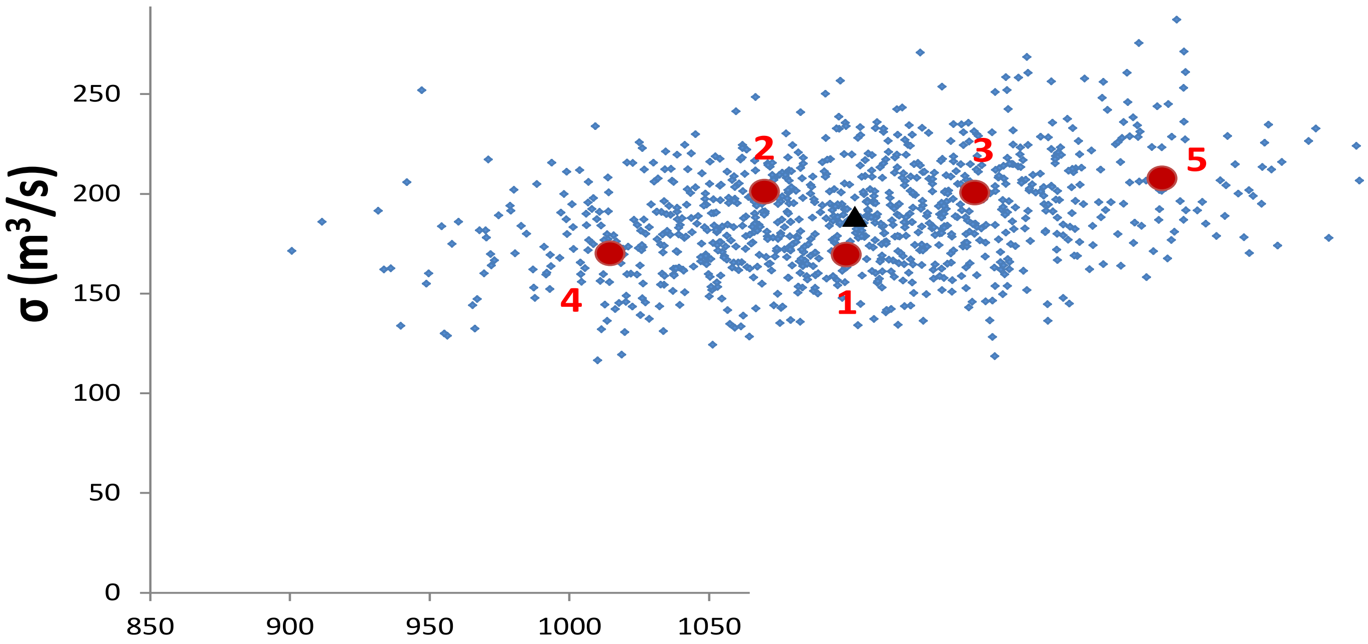
Motivation

- 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

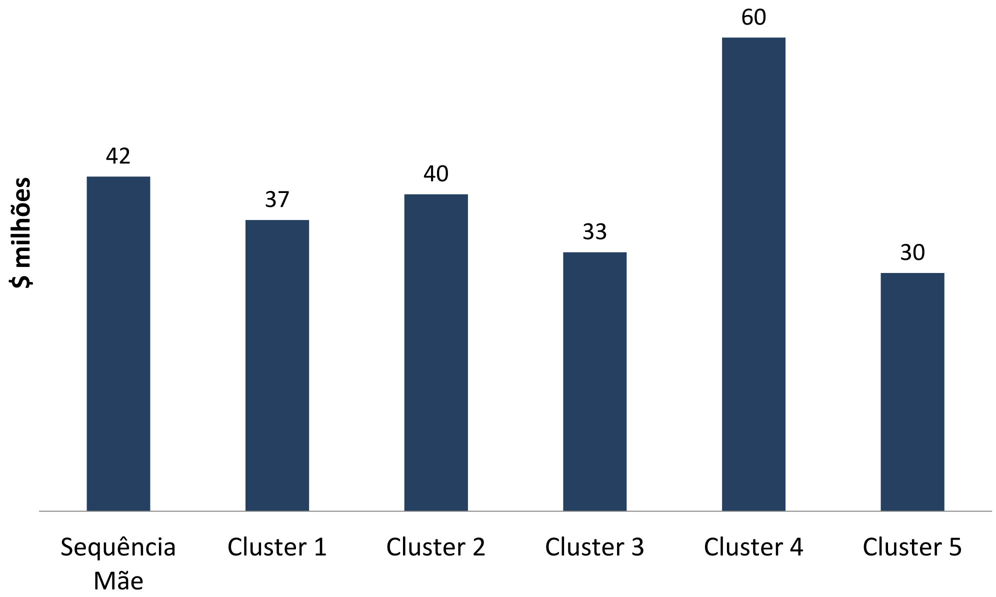
Generation of inflow scenarios with parameter uncertainty



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



Joint parameter estimation and stochastic optimization (Rockafellar)

- Model parameter selection
  - Calculate operating policies which are “taylor made” for each set of inflow model parameters $m = 1, \dots, M$, 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
- Ongoing research
  - Represent all the M alternative inflow models as part of the SDDP recursion
    - Interesting similarities to CVaR-cost in risk aversion

Watch Bernardo’s presentation!

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Motivation

- Expansion plans cannot capture an important attribute of different generation technologies: construction time
  - Hydro: 6+ years; thermal (gas): 4+ years; renewables: 1-2 years
- The ability to adjust construction of new generation to evolving conditions is especially relevant for developing economies
  - High, but very uncertain, load growth
  - In some countries, hydro storage is an important factor for reinforcements (e.g. recent three-year drought in Brazil)
  - Uncertainty on fuel costs also favors renewables

⇒ Interest in extending SDDP to represent investment variables

Development of planning strategies

- Markov chains are used to represent uncertainty in fuel costs and load growth rates (hybrid SDDP/SDP model)
- Handling nonconvexities due to binary investment decisions:

1. Hybrid plan/strategy
   - Hydro is a binary planning decision
     - Long construction times make plan ≈ strategy
   - Renewables are strategic continuous decisions
2. Tighter Lagrangian cuts in the SDDP recursion (Thomé 2013)

- Recent breakthrough: The excellent paper by Zou, Ahmed and Sun
  - The Lagrangian cuts are tight for binary variables!

Watch Fernanda's presentation!

In summary…

- Real-life applications of risk aversion in the energy area
- Multiscaling and parameter uncertainty are important issues for analysis of renewables
- Planning strategies are also important for renewables
  - Representation of construction times in multistage stochastic optimization
- Lagrangian + binary state variables are a very interesting new path for multistage stochastic planning

Topics not covered (lack of time)

- Representation of nonconvexities using Support Vector Regression (J.A.Dias)
- Power market modeling with multistage stochastic Nash Equilibrium (J.Garcia)
- Expansion planning with risk aversion (CVaR-cost) on operation (G.Rocha)
- Extension of Markov chains to fuel cost and demand growth uncertainties (R.Chabar)
- New techniques for multi-area reliability evaluation (G.Oliveira)
  - Cross Entropy + Monte Carlo Markov Chain
  - Allows feasibility cuts for planning models

THANK YOU
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