RECENT METHODOLOGICAL AND COMPUTATIONAL ADVANCES IN STOCHASTIC POWER SYSTEM PLANNING

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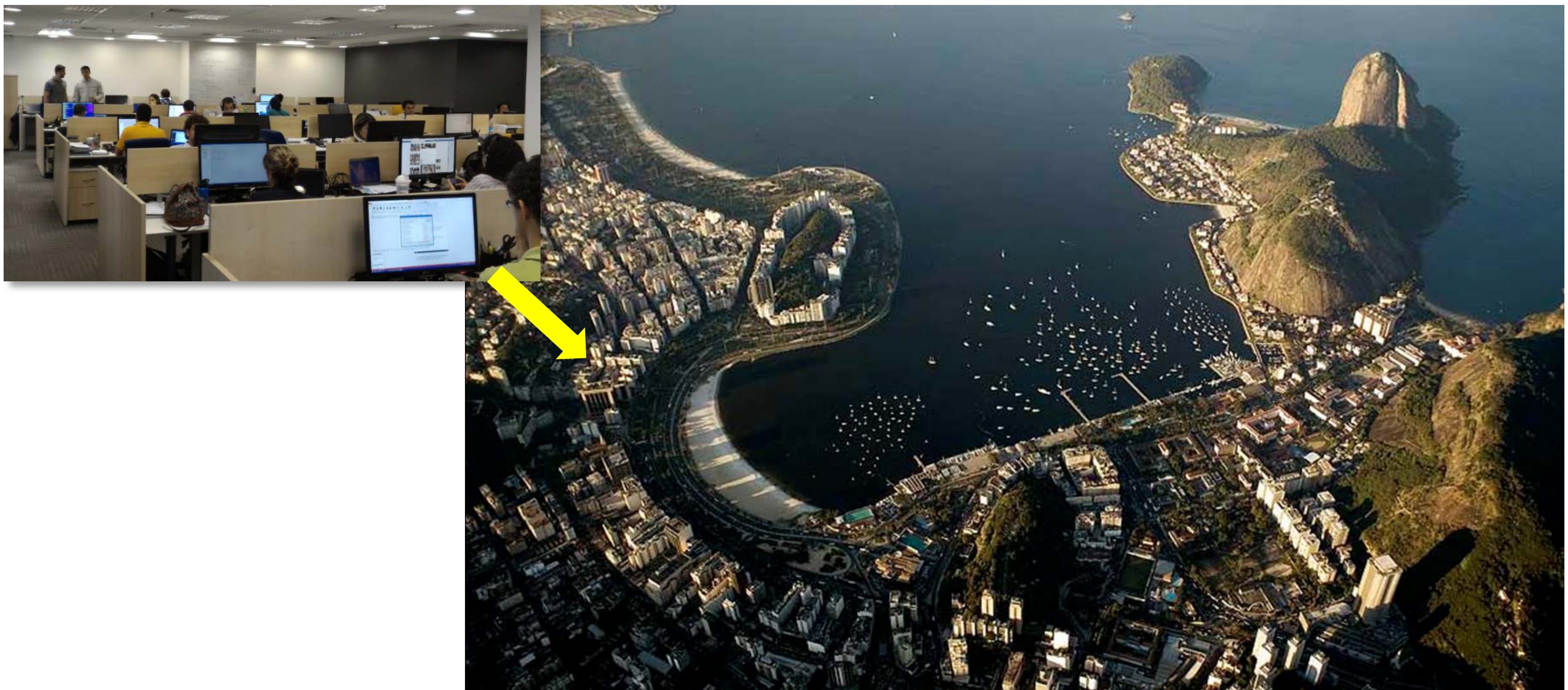
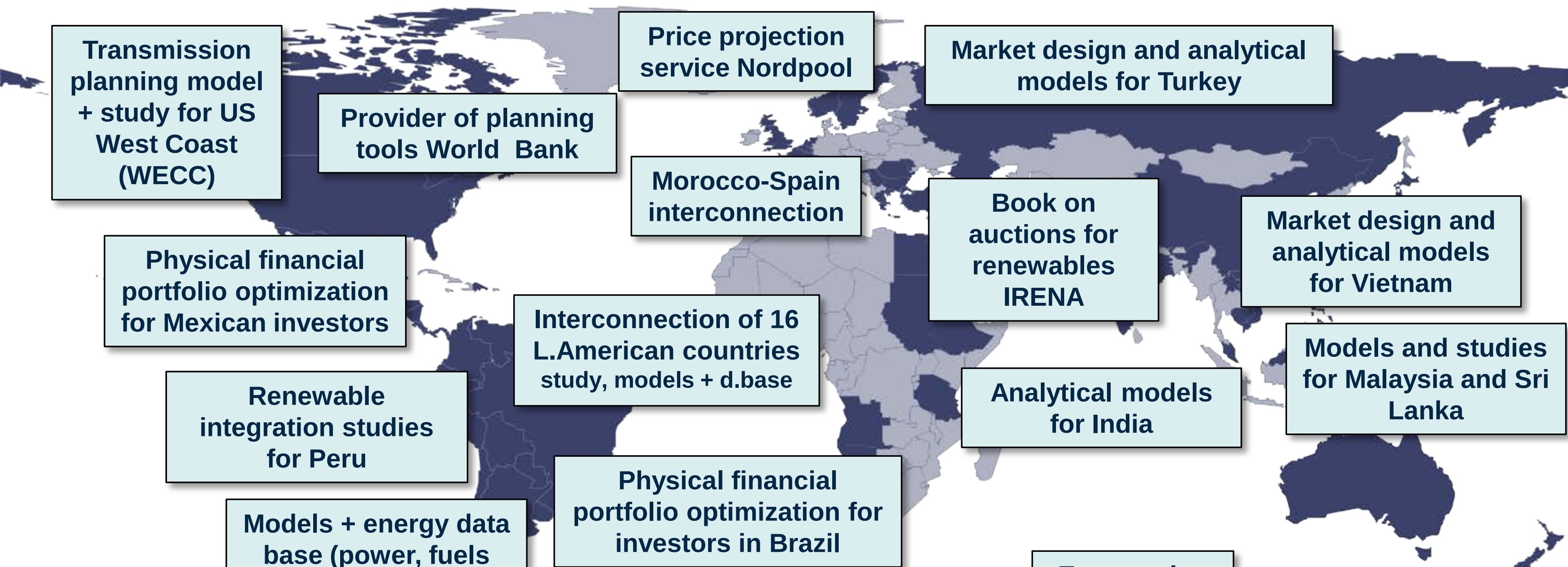
PSR

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



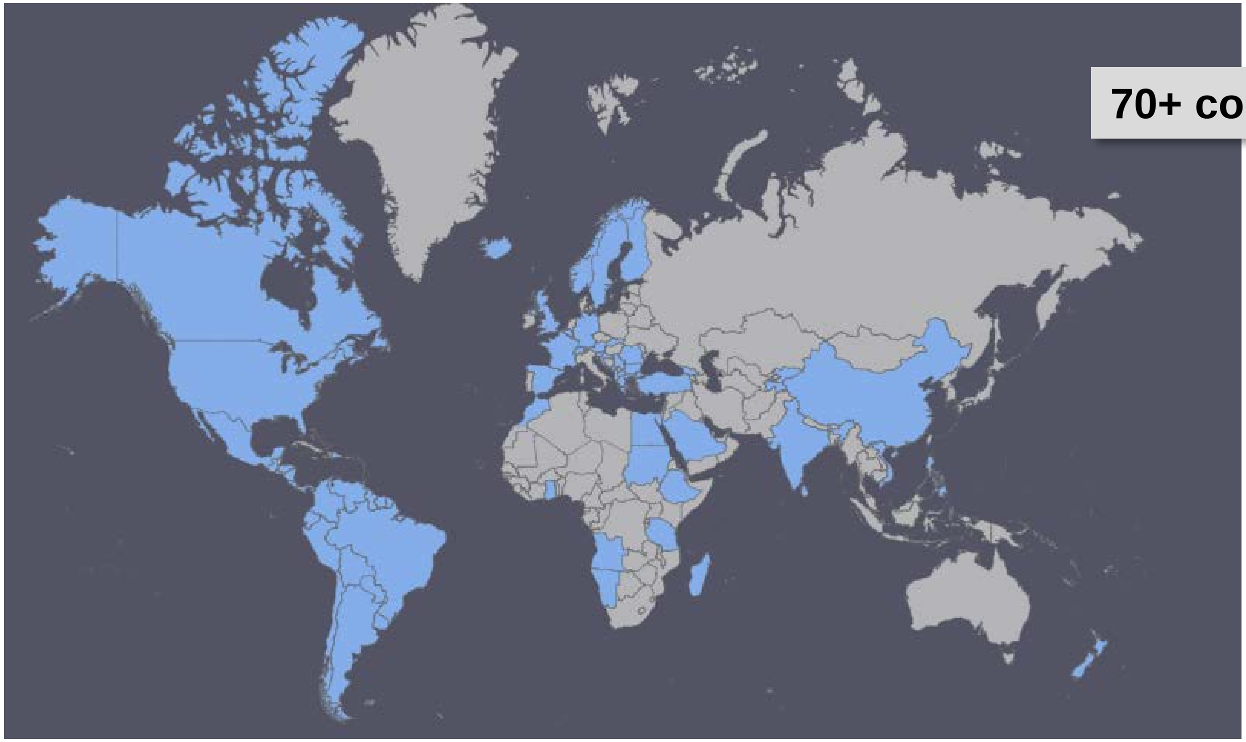
Some recent projects



Energy plan Mauritius

Energy plan Seychelles

Application of stochastic planning 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

Outline

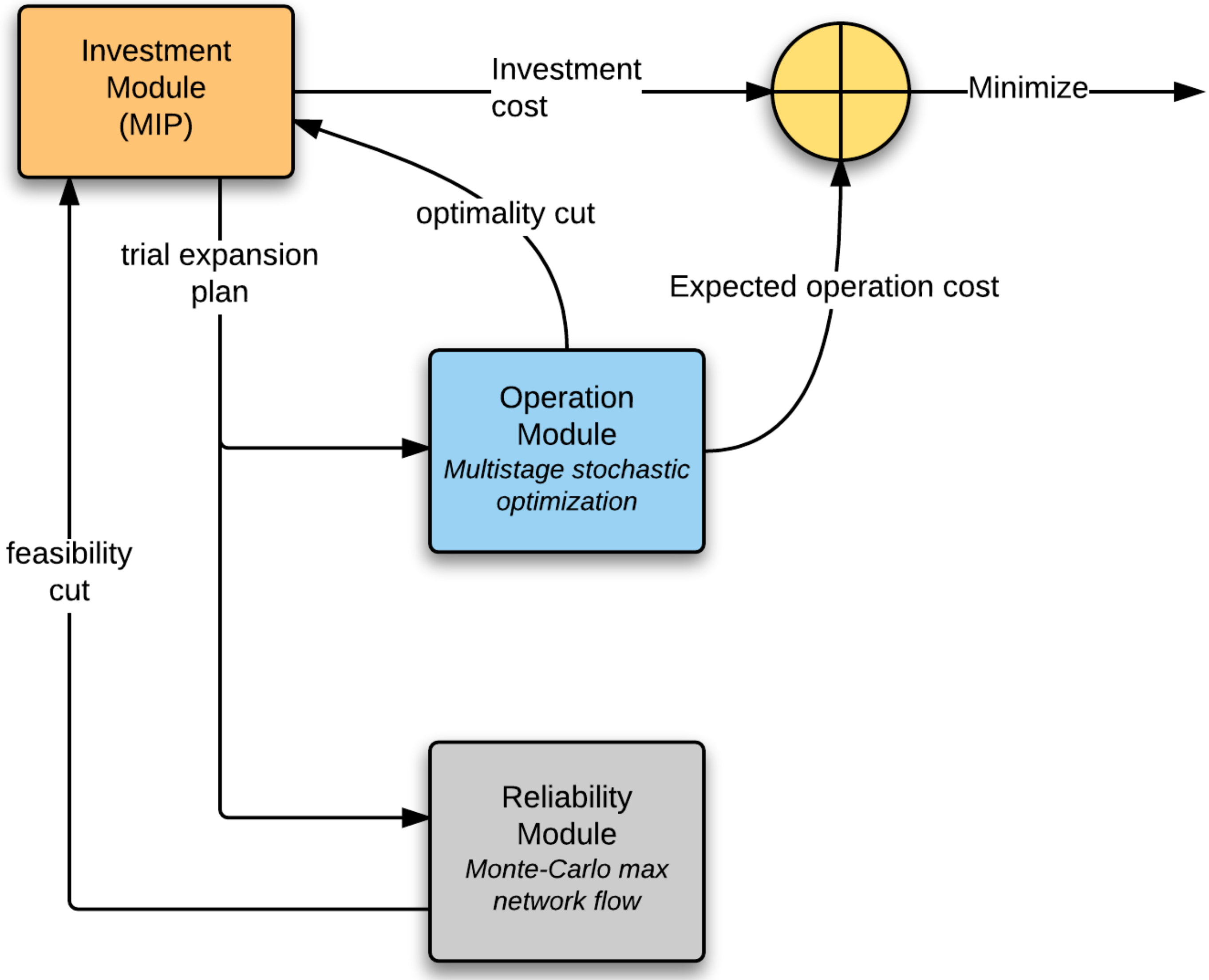
- Expansion planning problem formulation
  - Investment, operation and reliability modules

1. Operation module: SDDP
   - Analytical immediate cost function
2. Supply reliability module: CORAL
   - Use of GPUs and variance reduction
3. Investment module + complete expansion planning: OPTGEN/OPTNET
   - Case studies: Morocco + Spain; Bolivia; Central America

Power system planning

- Determine generation and transmission reinforcements required for the economic and reliable supply of predicted load
- Economic dimension: sum of investment and expected operation costs
- Two reliability dimensions: (i) rationing; and (ii) blackouts
  - Rationing (energy shortage): longer duration (days $\rightarrow$ months); (somewhat) predictable in advance; usually represented as a curtailment cost in the stochastic operations scheduling
  - Blackout (supply interruption): shorter duration (minutes $\rightarrow$ hours); (somewhat) unpredictable; usually represented as a supply reliability constraint (or target)

Problem formulation: Benders decomposition



Part 1: Operation module (SDDP)

- Weekly or monthly time steps; 25+ years horizon
  - Intra-stage: 5-21 load blocks to 168-730 hours
- Detailed generation modeling: renewables (hydro, wind, solar biomass etc.), storage (hydro reservoirs, pumped storage etc.), thermal plants (gas, oil, nuclear etc.) and others
- 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

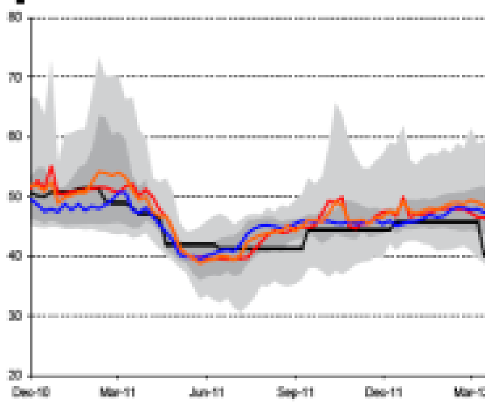
Week

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 - 2011



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.

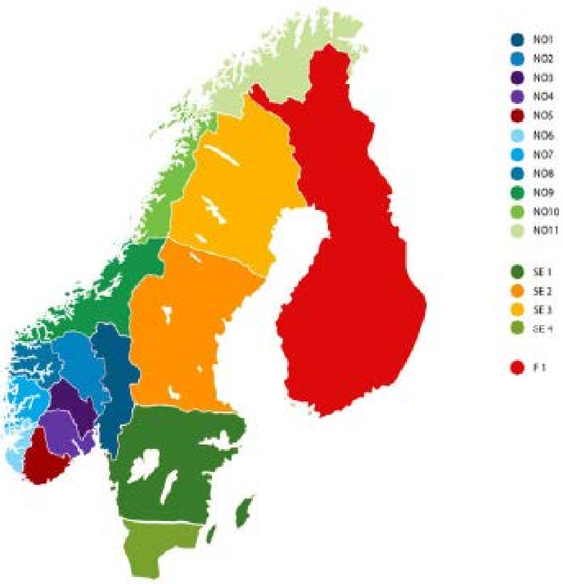


Figure 1: New hydro regions as modeled in the HBV and SDDP models. Notice that the hydro regions for Norway are not identical to the price regions (NO1-5).

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

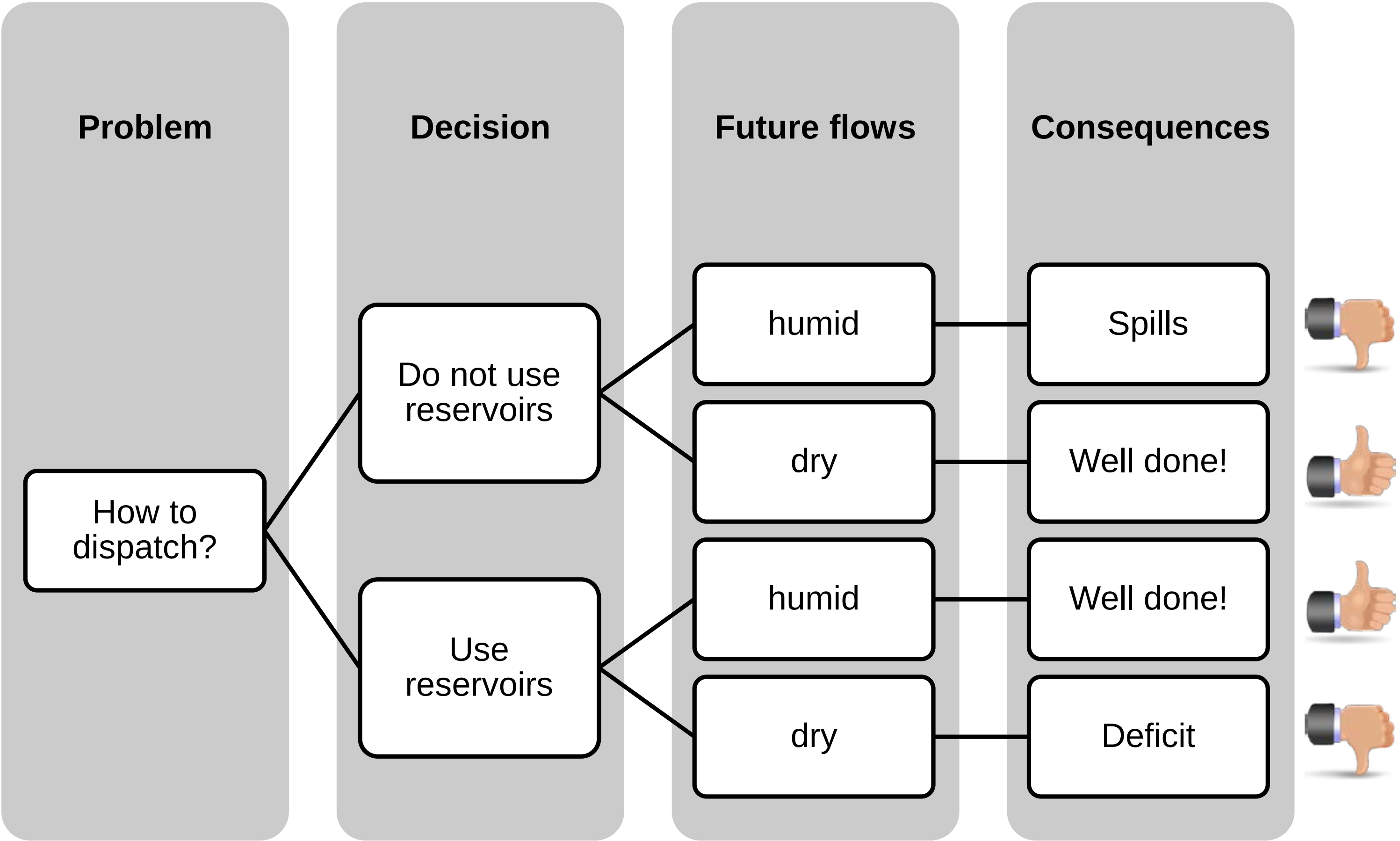
Solution algorithm: stochastic dual dynamic programming (SDDP)

- 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

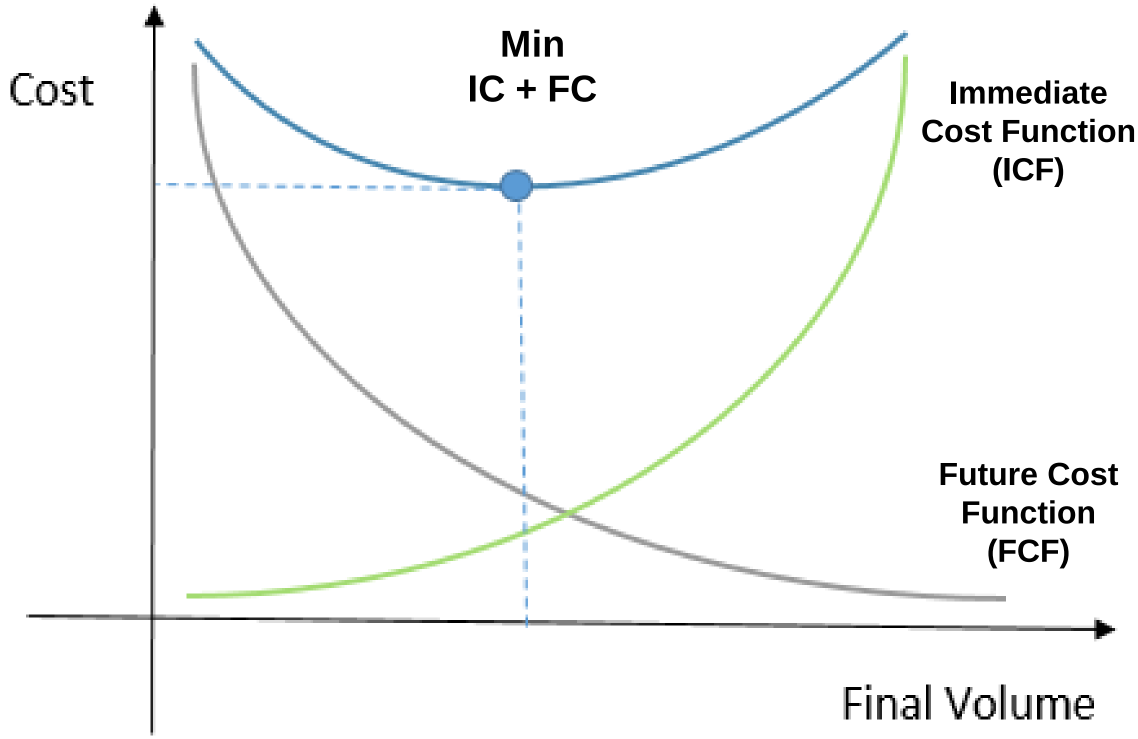
The stochastic optimizer's dilemma



Challenge: the decision tree for a real life scheduling problem with a five-year horizon (60 monthly steps) would have 10^{100} nodes

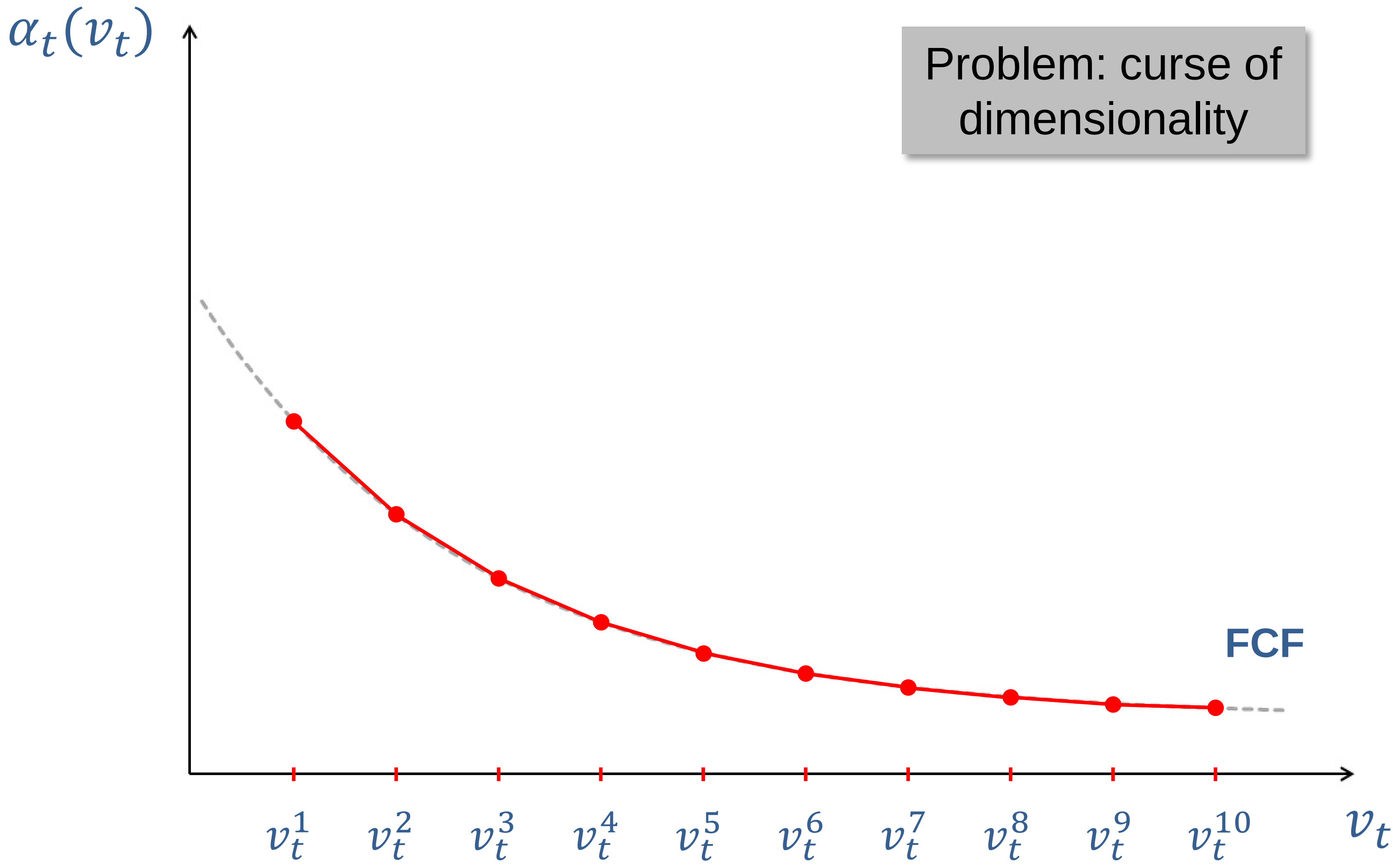
Stochastic Dynamic Programming

- State space formulation
- Decomposition in time stages



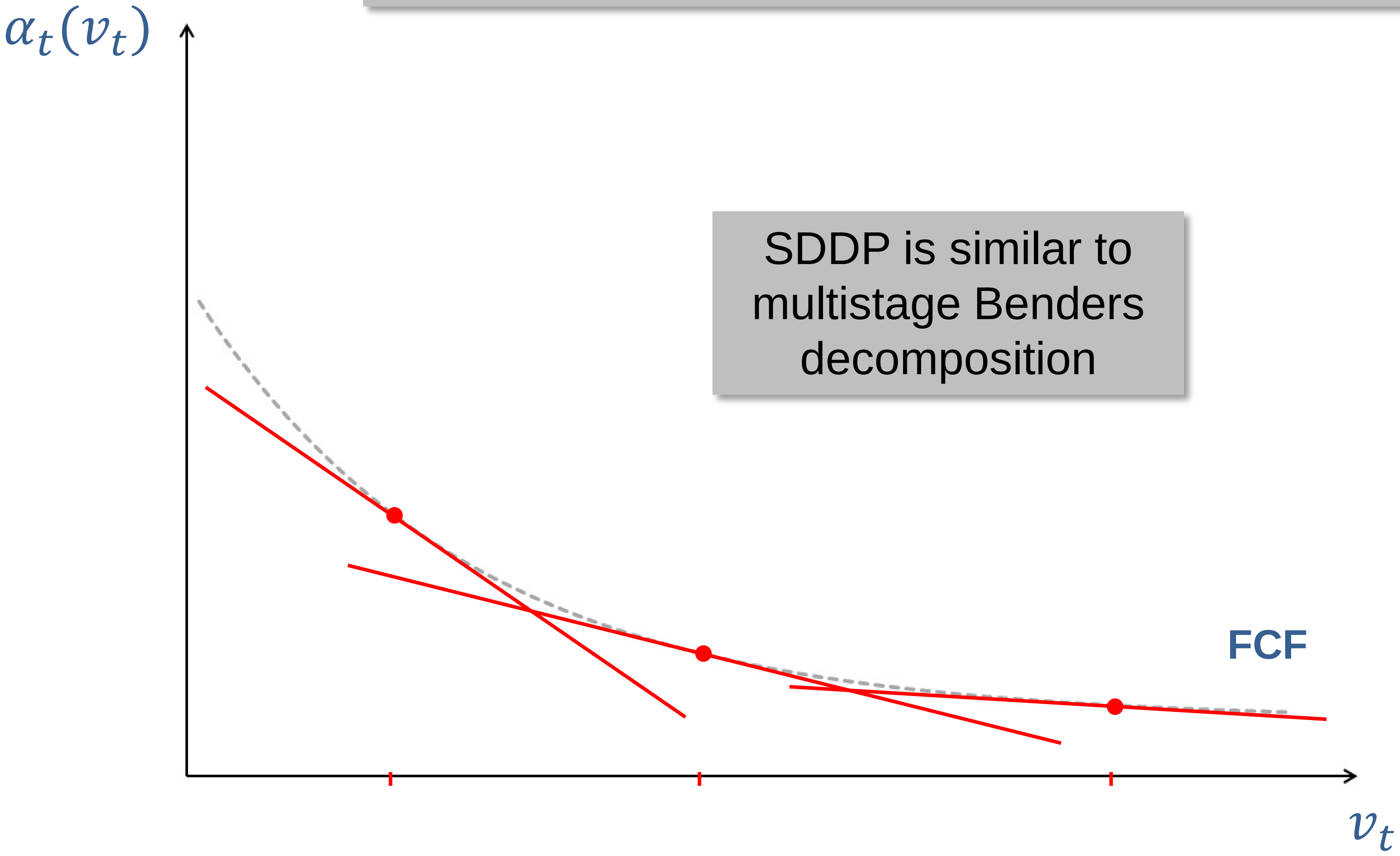
Traditional approach: discretize states

Problem: curse of dimensionality



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 (very simplified)

- Objective function (min immediate cost + future cost)

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

- Storage balance & hydro production

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

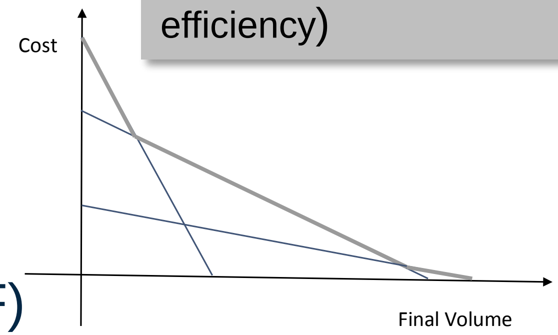
$$\sum_\tau e_{t\tau i} = \rho_i u_{t,i}$$

- Power balance

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

$$\forall \tau = 1, \dots, \mathrm{T}$$

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



- (piecewise linear) 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

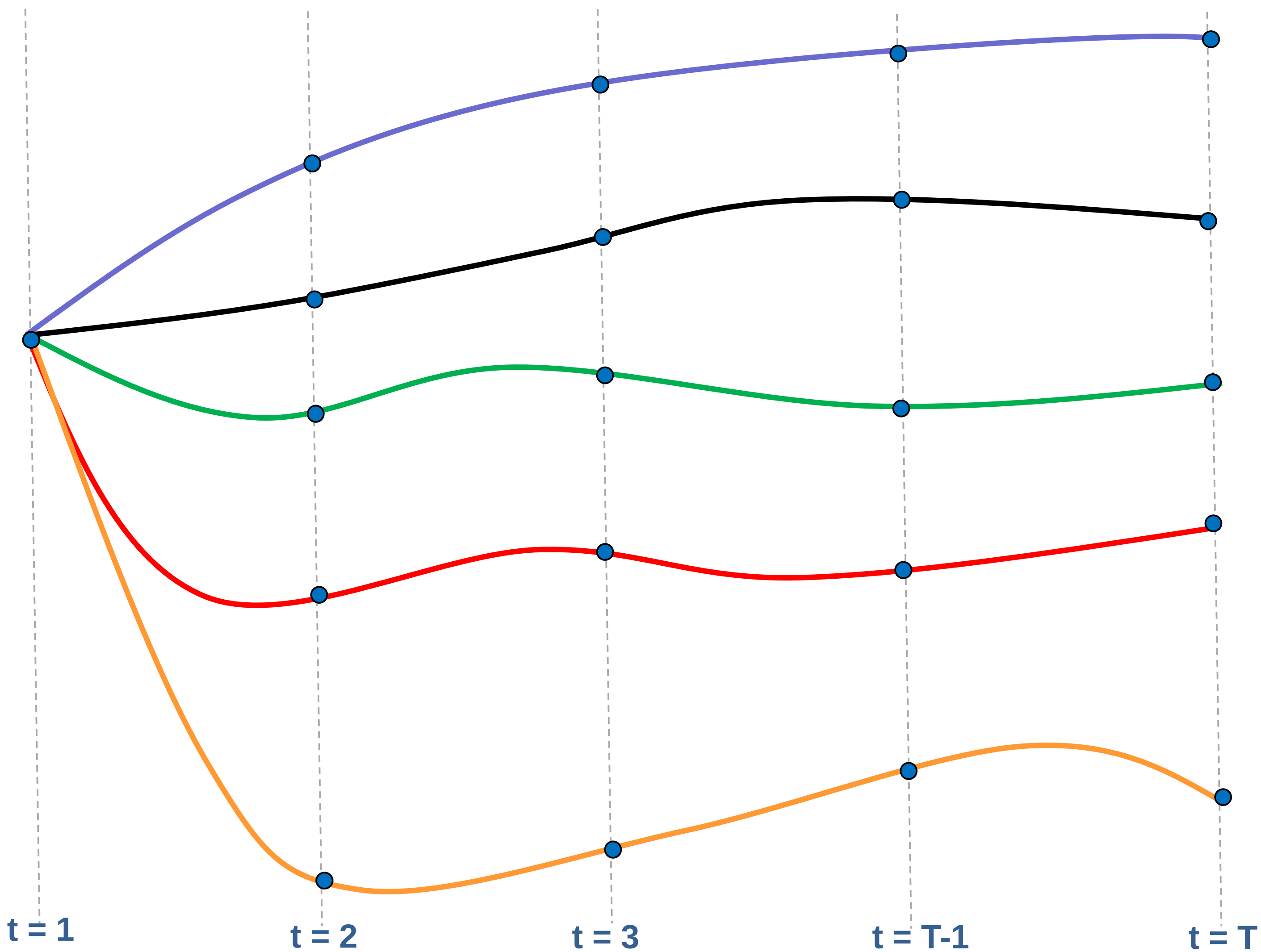
Iterative procedure

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

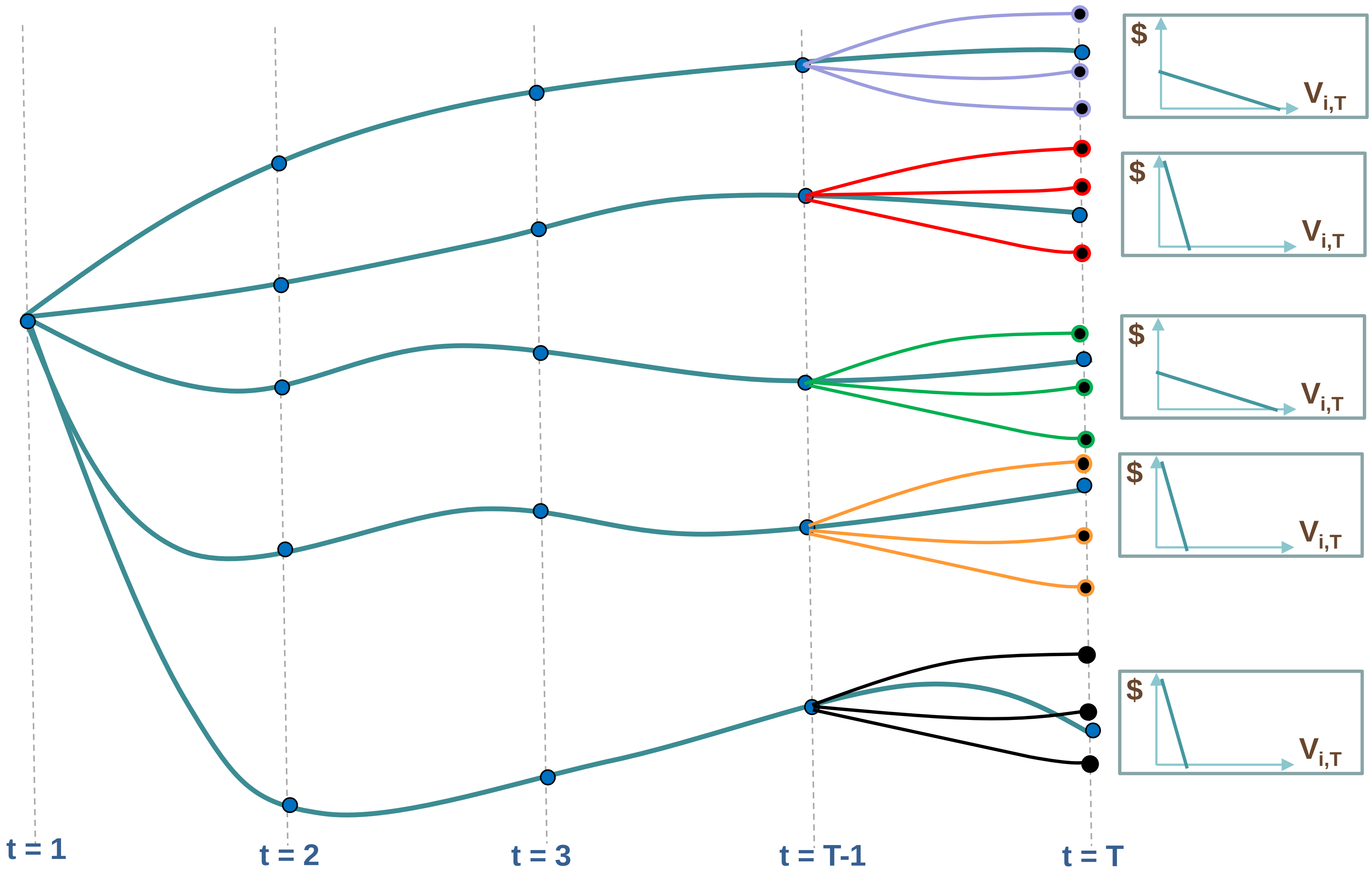
Distributed processing

- 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 plants (85 with storage), 140 thermal plants (gas, coal, oil and nuclear), 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

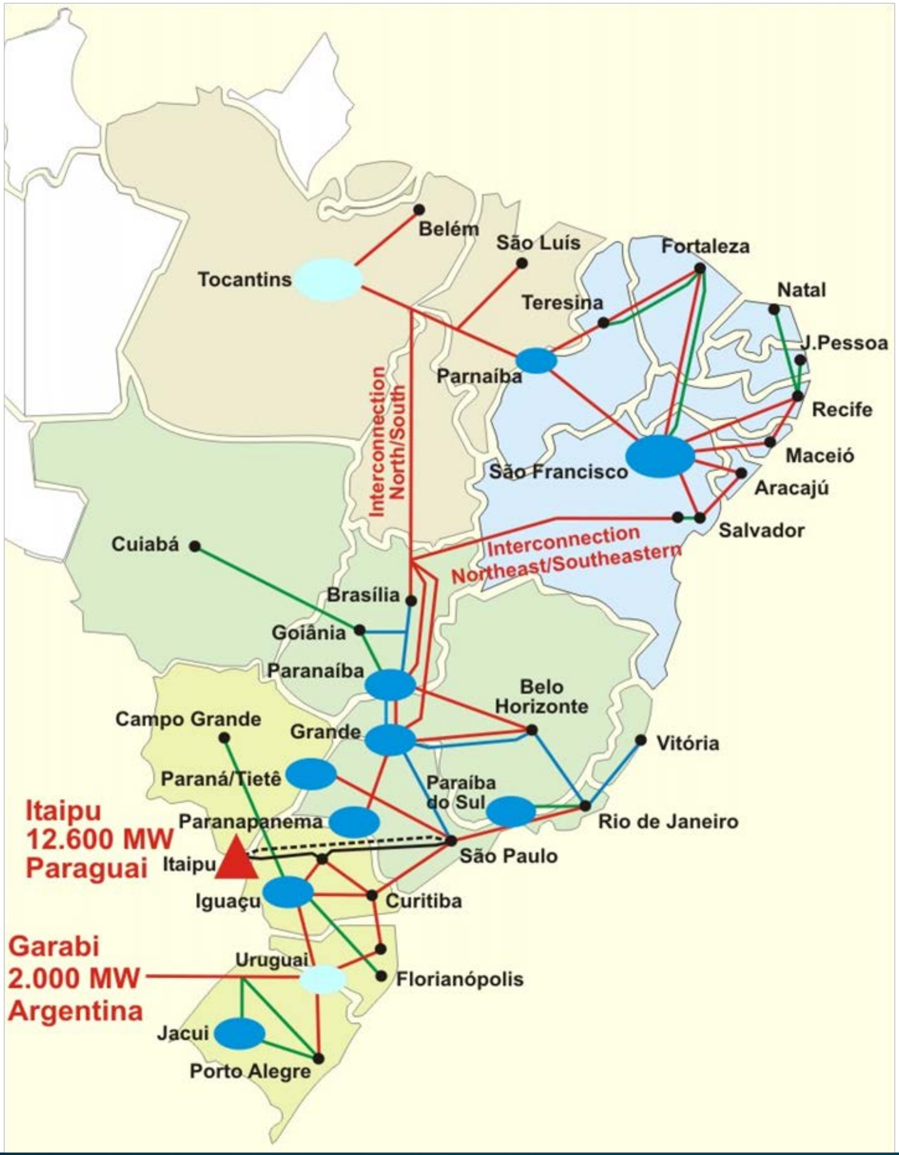
Forward scenarios: 1,200

Backward branching: 30

LP problems per stage/iteration: 36,000

Number of SDDP iterations: 10

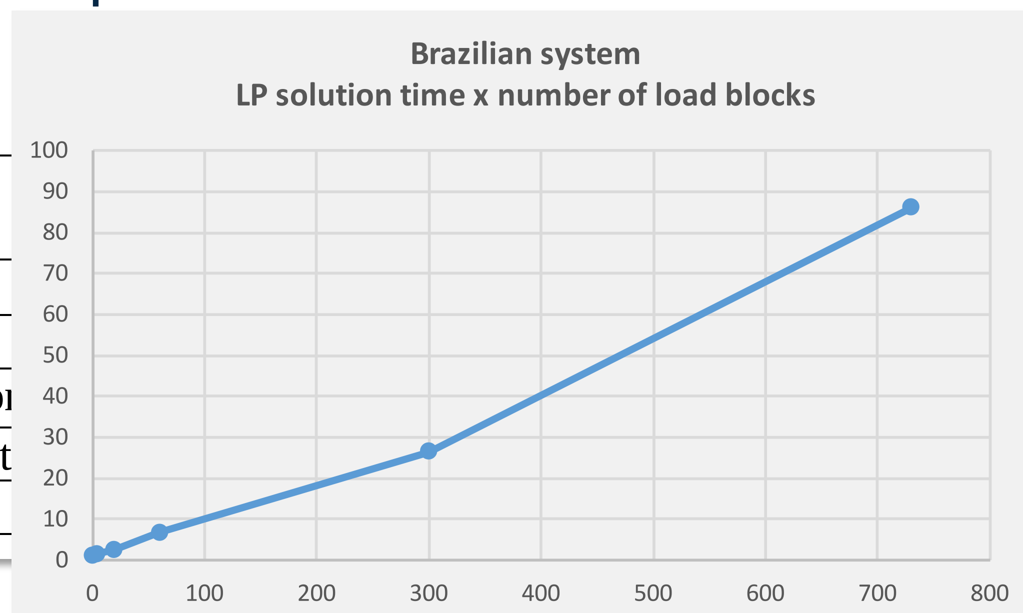
Total execution time: 90 minutes
25 servers with 16 processors each



Recent SDDP development: analytical ICF

- 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 hourly (or shorter) intervals in the intra-stage operation model ⇒ increase in computational effort

Constraints
Water balance constraints
Load balance constraints
Maximum generation & turbining co
Maximum & minimum volume const
Total



One-stage problem with analytical ICF

- Objective function (min immediate cost + future cost)

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

- Storage balance

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

$$e_{t,i} = \rho_i u_{t,i}$$

- FCF

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

- (piecewise linear) Immediate Cost Function (ICF)

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

> - Problem size is the same for any duration of intra-stage intervals
> - 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

- The analytical ICF can be seen as a multiscaling technique: the weekly (or monthly) operation problem represents explicitly the variables with slower dynamics, in particular, the storage state variables; the faster dynamics (hourly balance) are represented implicitly in the ICF
- The idea is to pre-calculate all vertices (breakpoints) of the piecewise function $\beta_t(e_t)$ and transform them into hyperplanes

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

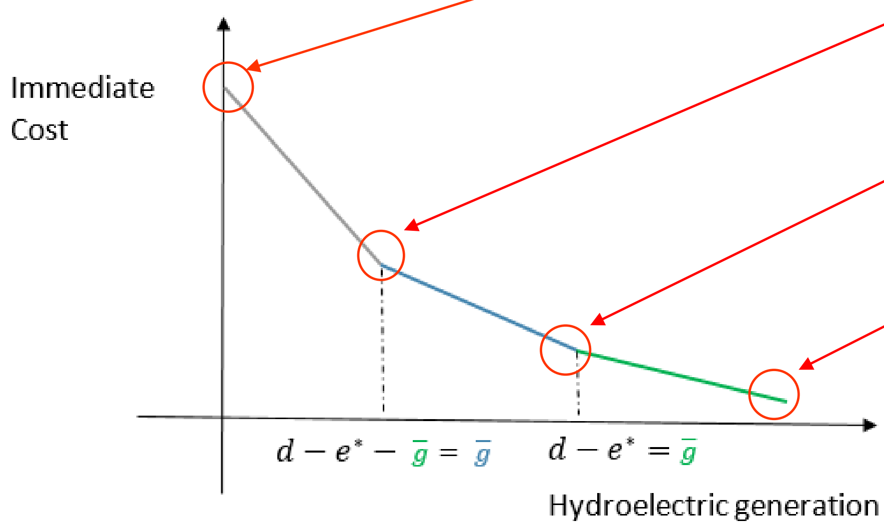
$$\sum_\tau e_{t\tau} = e_t \quad \leftarrow \text{coupling constraint}$$

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

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

ICF calculation (1/2): inspired by "load duration curve" (LDC) probabilistic production costing techniques (1980s)

1. Lagrangian relaxation: a "water value" decomposes $\beta_t(e_t)$ into T "economic dispatch" (ED) subproblems with J thermal plants + 1 dummy plant (hydro)
   - There are only $J + 1$ different water values, corresponding to the different positions of the hydro plant in the "loading order"
   - **Only the first and last water values need to be used**



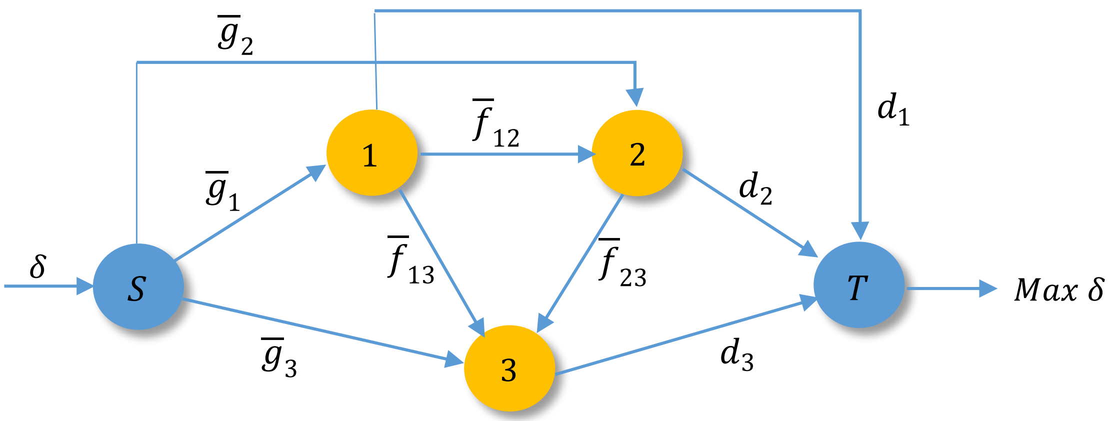
Solution approach (2/2)

2. Each ED subproblem is further decomposed into $J + 1$ *generation adequacy* subproblems, where we just compare available capacity with (demand – renewables) (arithmetic operation)
   - Expected thermal generation of plant j (in the loading order) = (EPNS without j) – (EPNS with j)

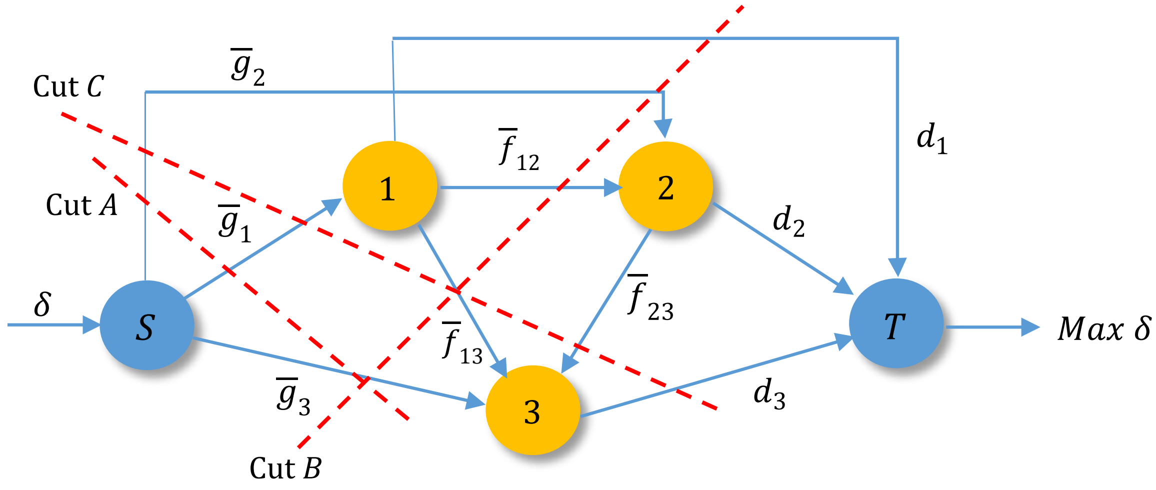
$\Rightarrow$ Computational effort is very small
(and can be done in parallel)

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

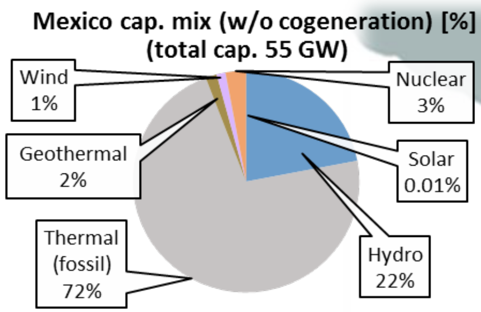
- The multiarea generation adequacy is a max-flow problem



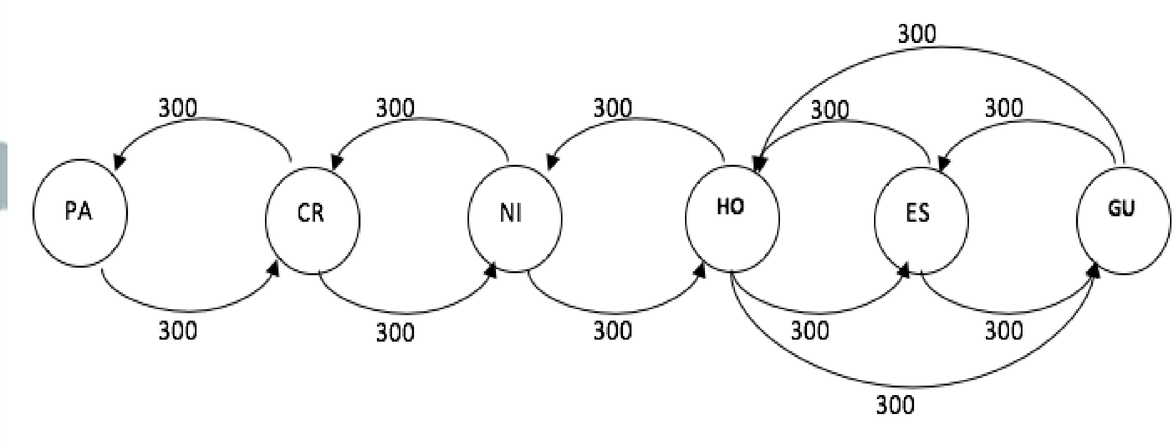
- Max flow – min cut ⇒ problem becomes max {2^M linear segments}

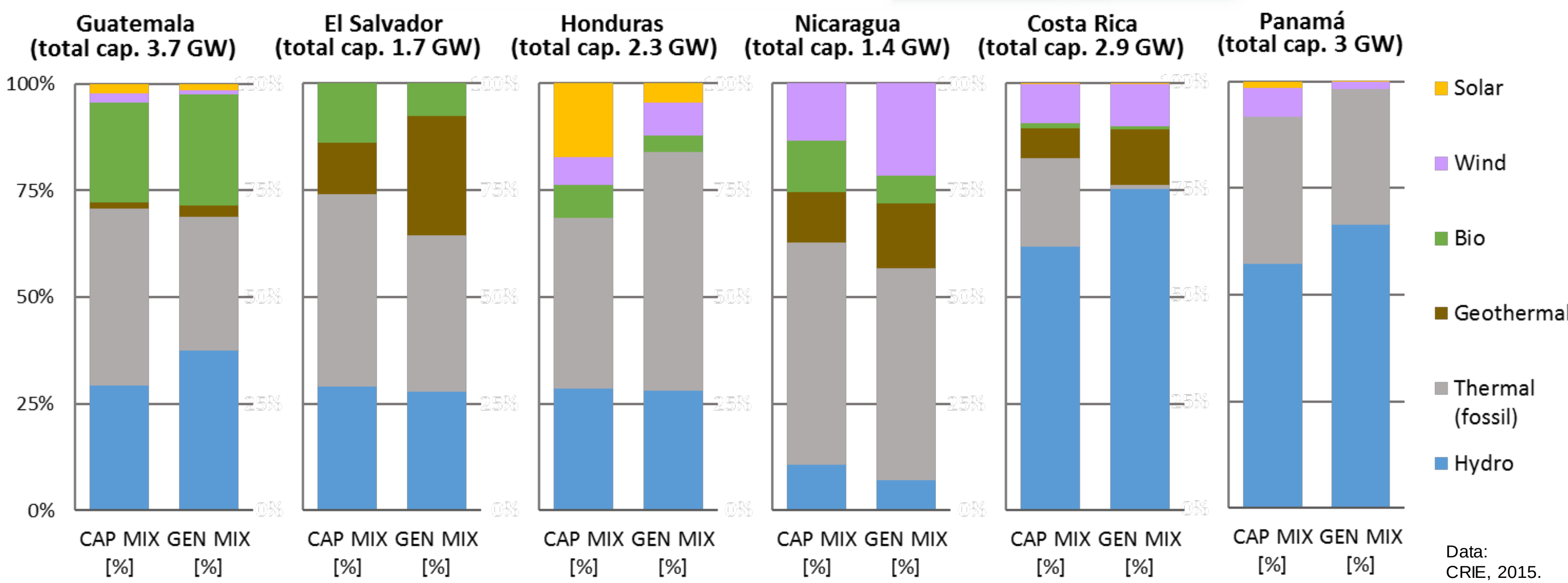


Example: Central America



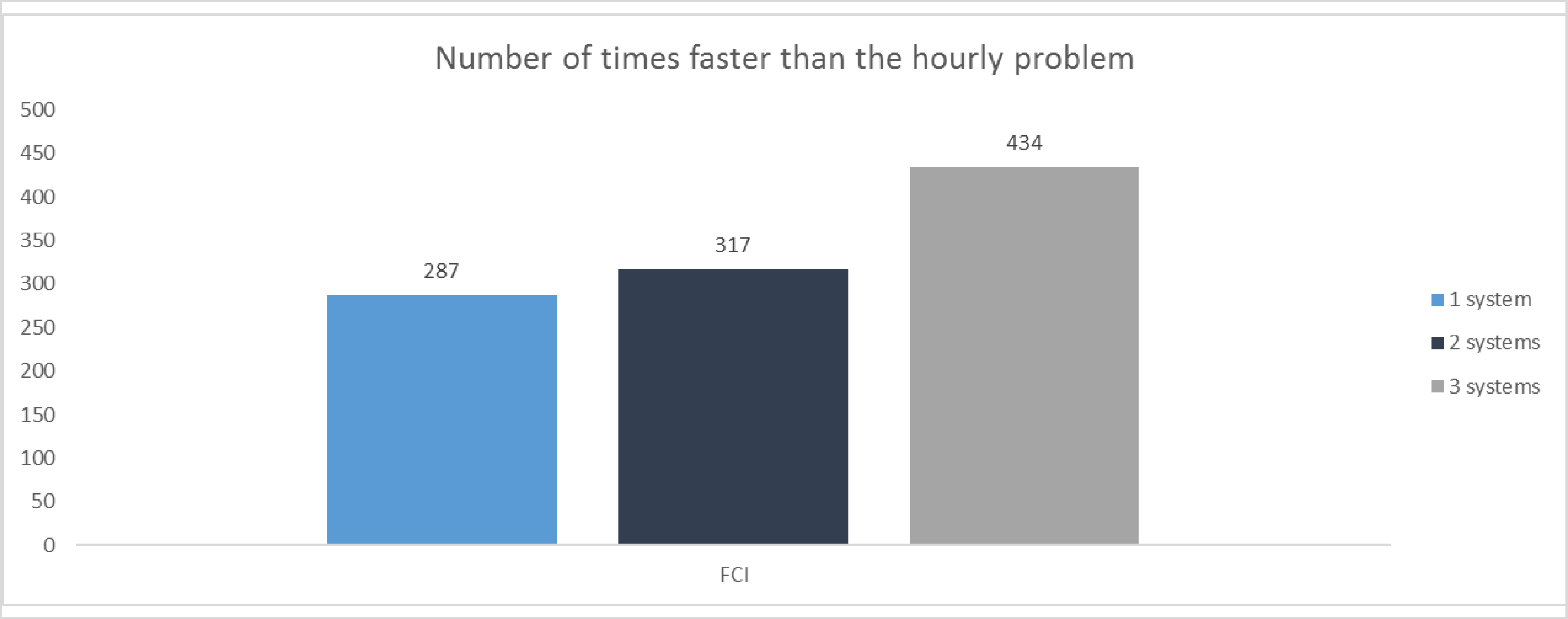
Data: SENER, 2016.





Data: CRIE, 2015.

SDDP execution time with/without analytical ICF

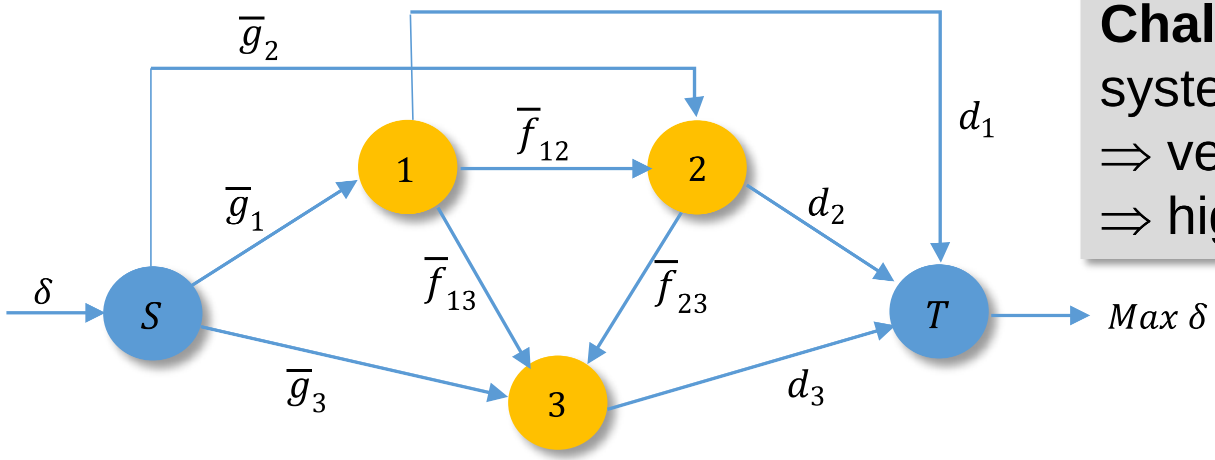


Current research

- 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

Part 2: Supply reliability module (CORAL)

- Randomly sample $s = 1, \dots, S$ scenarios
  - Equipment outages, load levels and renewable production
- Solve the multiarea supply problem for scenario s

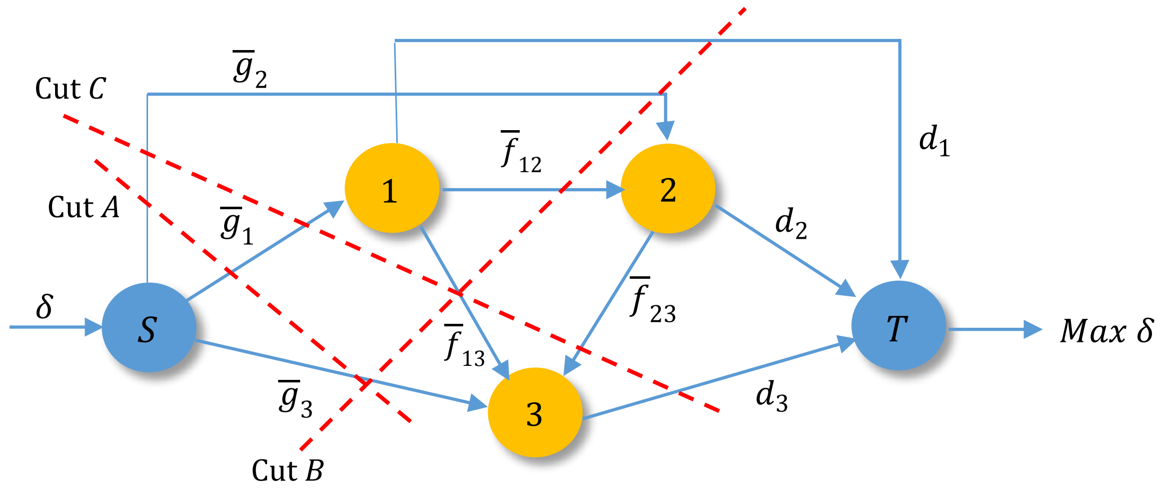


Challenge: real power systems are very reliable
$\Rightarrow$ very large sample size S
$\Rightarrow$ high computational effort

- Power not supplied $\varepsilon^s = \sum_m \hat{d}_m^s - \delta^s$
- Expected power not supplied $EPNS = \frac{1}{S} \sum_s \varepsilon^s$

Recent advances: GPUs

- GPUs can provide a very large amount of numerical processing capacity for a comparatively low price
- Limitation: GPUs are optimized for algebraic operations $(Ax^s = b^s, s = 1, \ldots, S)$
- Max-flow min cut allows GPU application to multi-area reliability



Example: same Central America system

- Notebook: I7 processor (2.4GHz) and a 384-core GPU

Sample size (millions)	CPU (secs)	GPU (secs)	Speedup
0.1	24.2	3.7	6.5
1.0	134.3	4.4	30.7
10.0	1,210.1	13.8	87.4
20.3	2,450.0	23.4	104.5
40.6	4,900.0	39.5	123.9

- Amazon server: Xeon 2 CPU (2.66 GHz); 1,536 core GPU

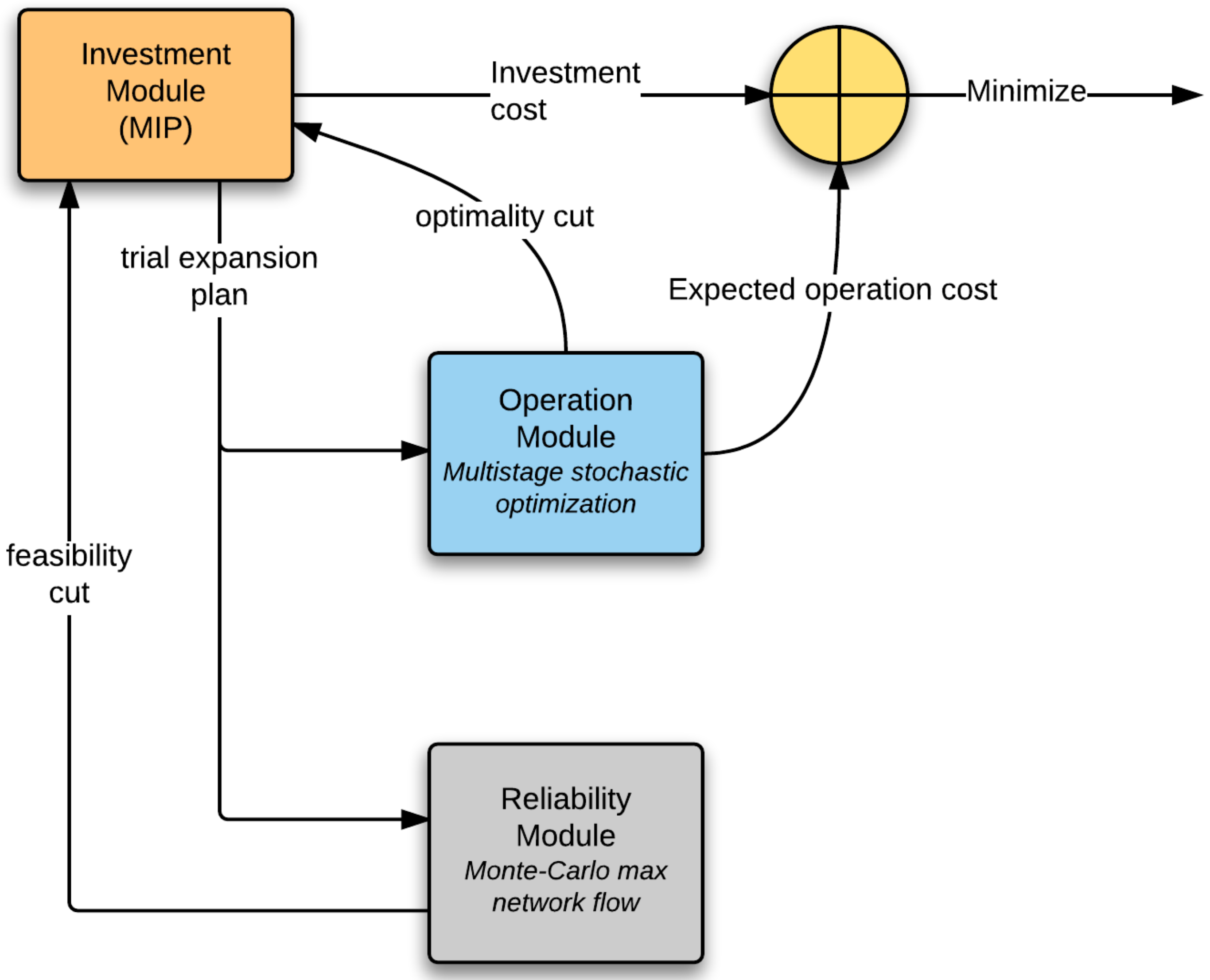
Sample size (millions)	CPU (secs)	GPU (secs)	Speedup
0.1	15.7	1.8	8.8
1.0	127.9	2.1	62.1
10.0	1,249.9	6.1	206.6
20.3	2,469.0	9.0	274.3
40.6	4,938.0	15.6	316.5

New Amazon server: 16 GPUs with 192 GB memory and 40,000 cores (!)

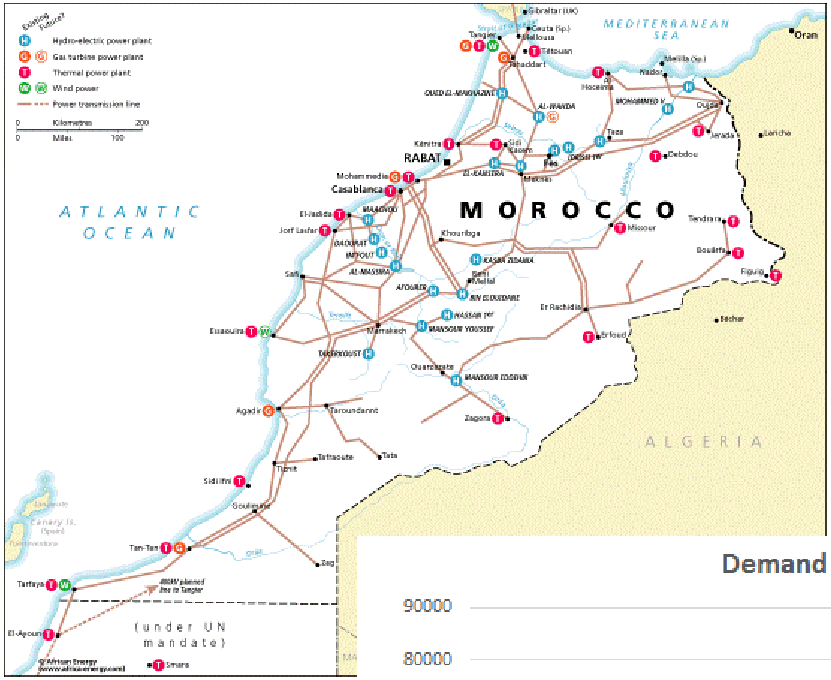
Current research

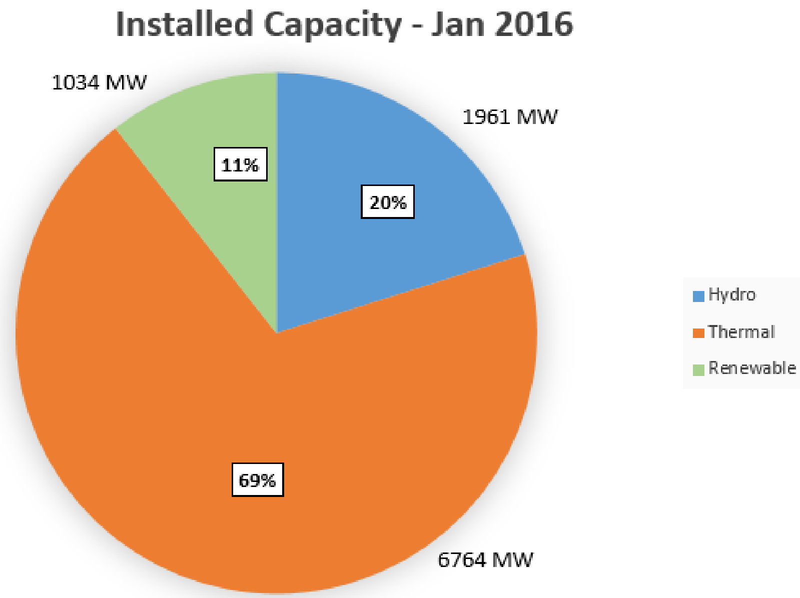
- Application of GPUs to SDDP’s analytical ICF and FCF
  - Both require calculation of Max {set of hyperplanes}
- Integrated variance reduction techniques: Monte Carlo Markov Chain (MCMC) provides the “calibration set” for Cross Entropy
  - Gains of two-three orders of magnitude

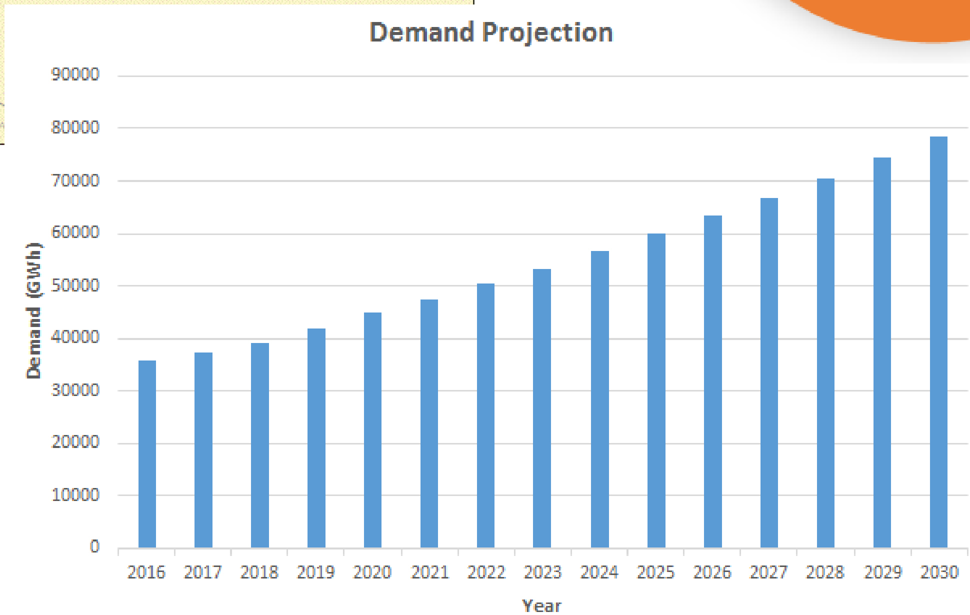
Part 3: complete Benders decomposition scheme



Example 1: Morocco-Spain expansion plan

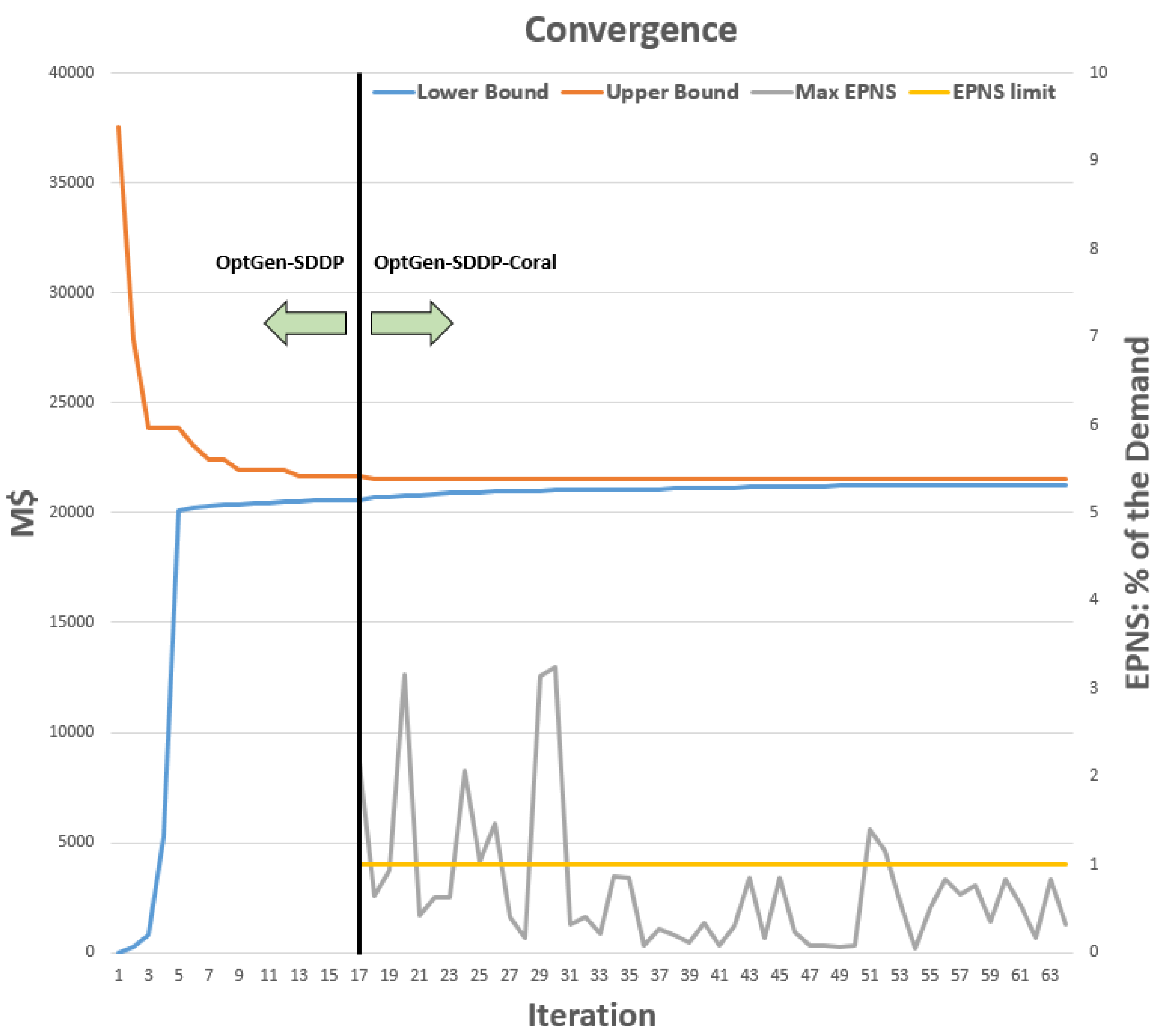






Planning horizon: 15 years
Yearly investment decisions
780 weekly operation stages (21 load blocks in each stage)

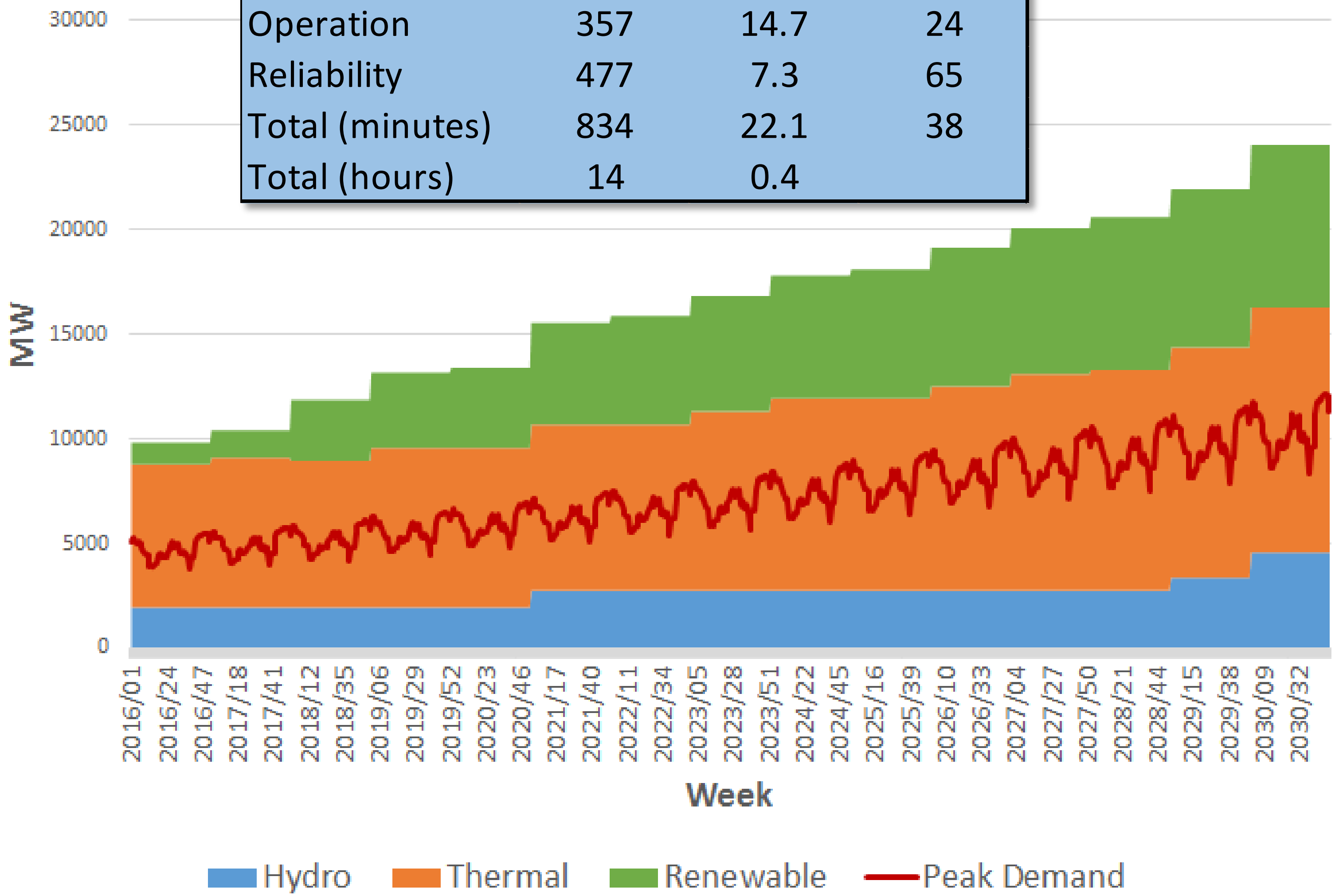
Convergence of Benders decomposition



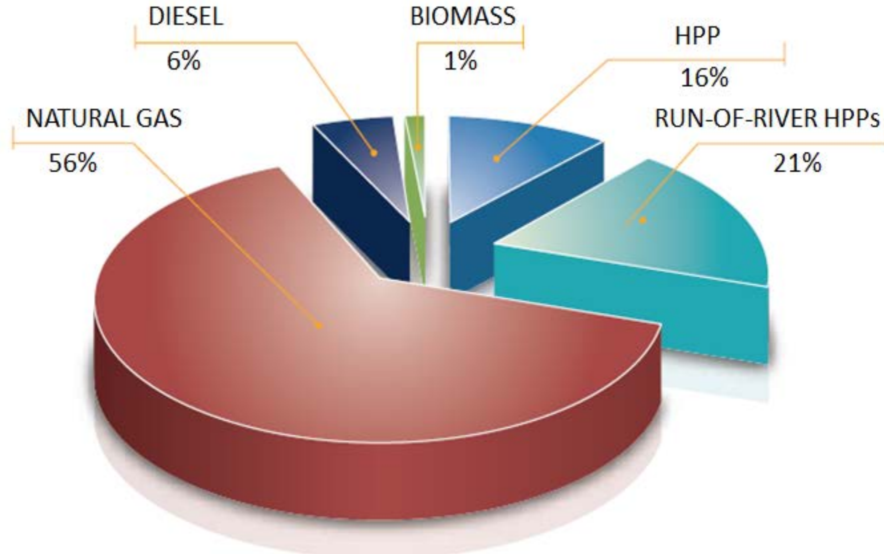
Optimal expansion plan + execution time

Execution time

(16 processes)	Standard	ICF+ GPU	Speedup
Operation	357	14.7	24
Reliability	477	7.3	65
Total (minutes)	834	22.1	38
Total (hours)	14	0.4	

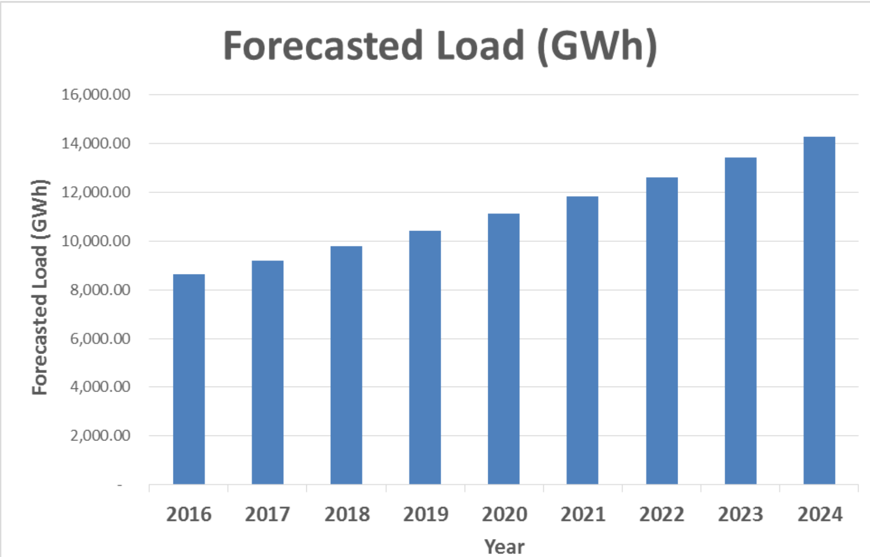


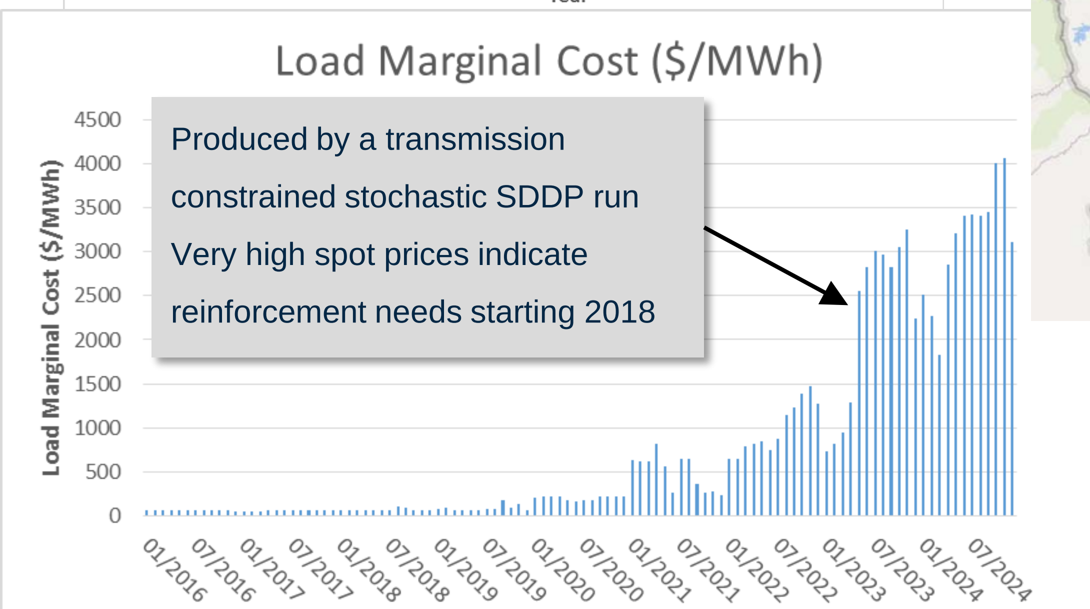
Example 2: Bolivia integrated G&T planning (1/4)



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

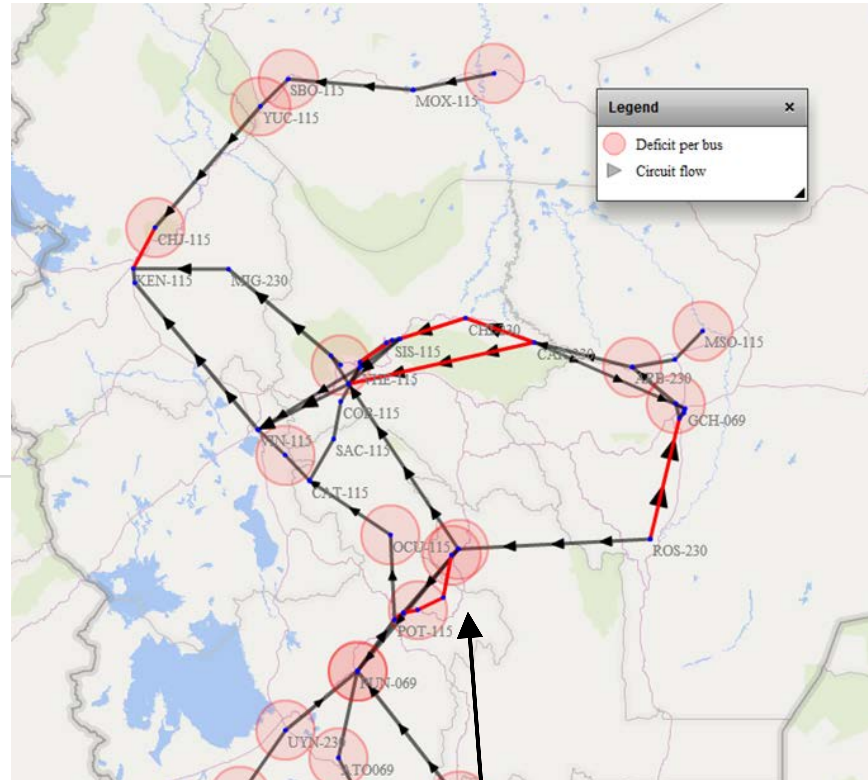
Bolivia integrated G&T planning (2/4)





Produced by a transmission constrained stochastic SDDP run

Very high spot prices indicate reinforcement needs starting 2018



Buses with deficit

Lines at the maximum loading

Bolivia integrated G&T planning (3/4)

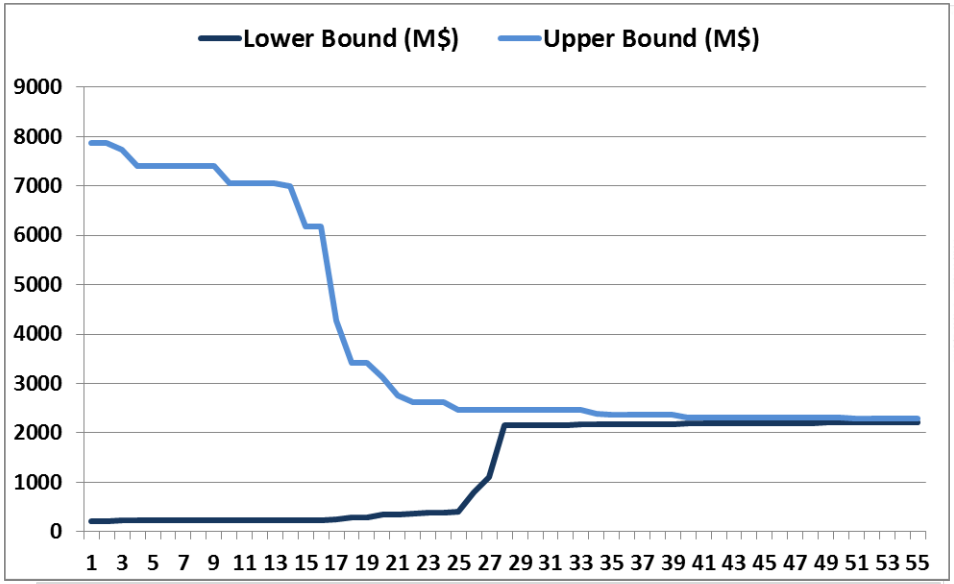
Study parameters

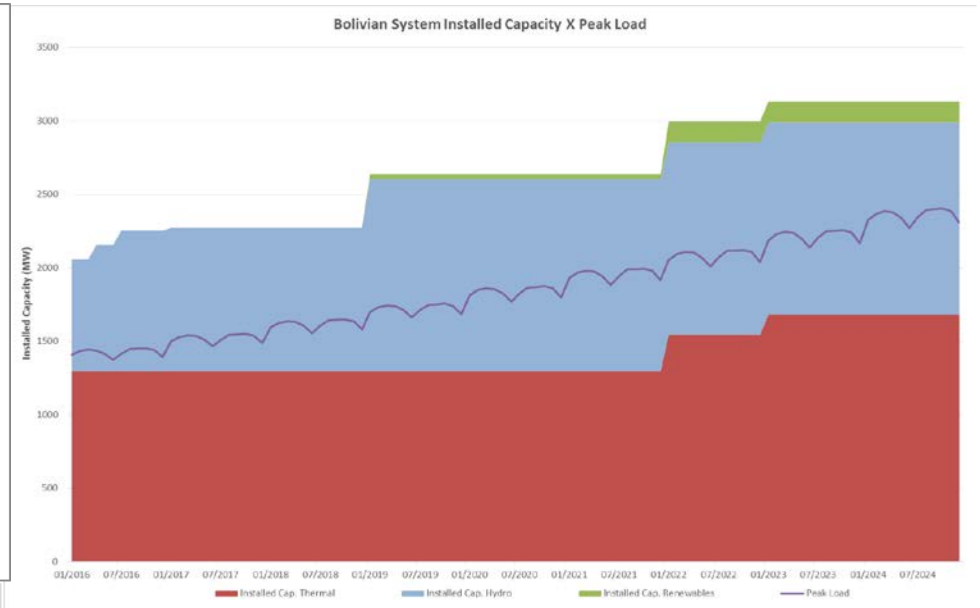
- Horizon: 2016-2024 (108 stages)
- 86 candidate projects per year (x 9 years)
  - 27 thermal plants (natural gas, combined and open cycle)
  - 8 hydro plants
  - 7 renewable projects (4 wind farms and 3 solar)
  - 44 transmission lines and transformers

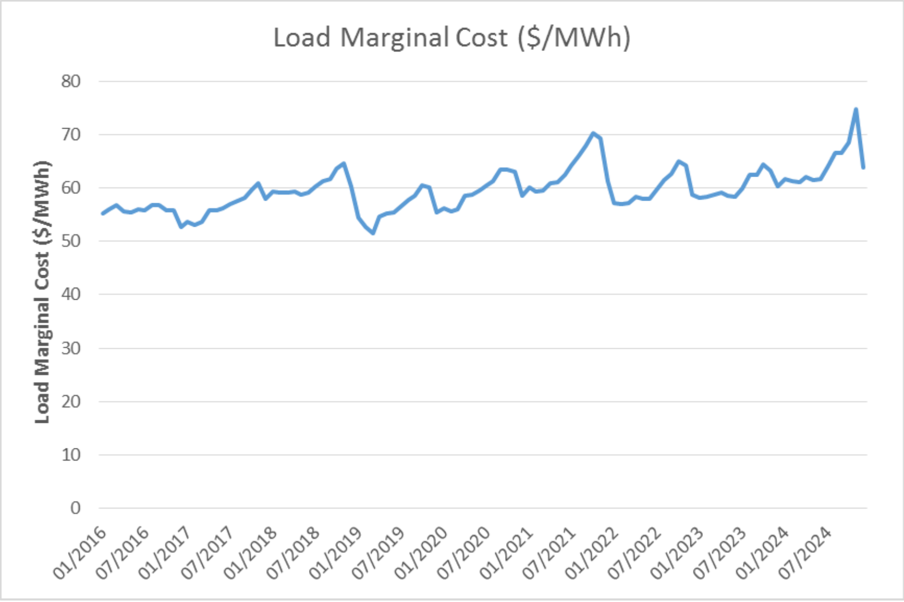
Computational results

- Number of Benders iterations (investment module): 55
- 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: 4h 20m
  - 2 servers x 16 processors = 32 CPUs

Bolivia integrated G&T planning (4/4)





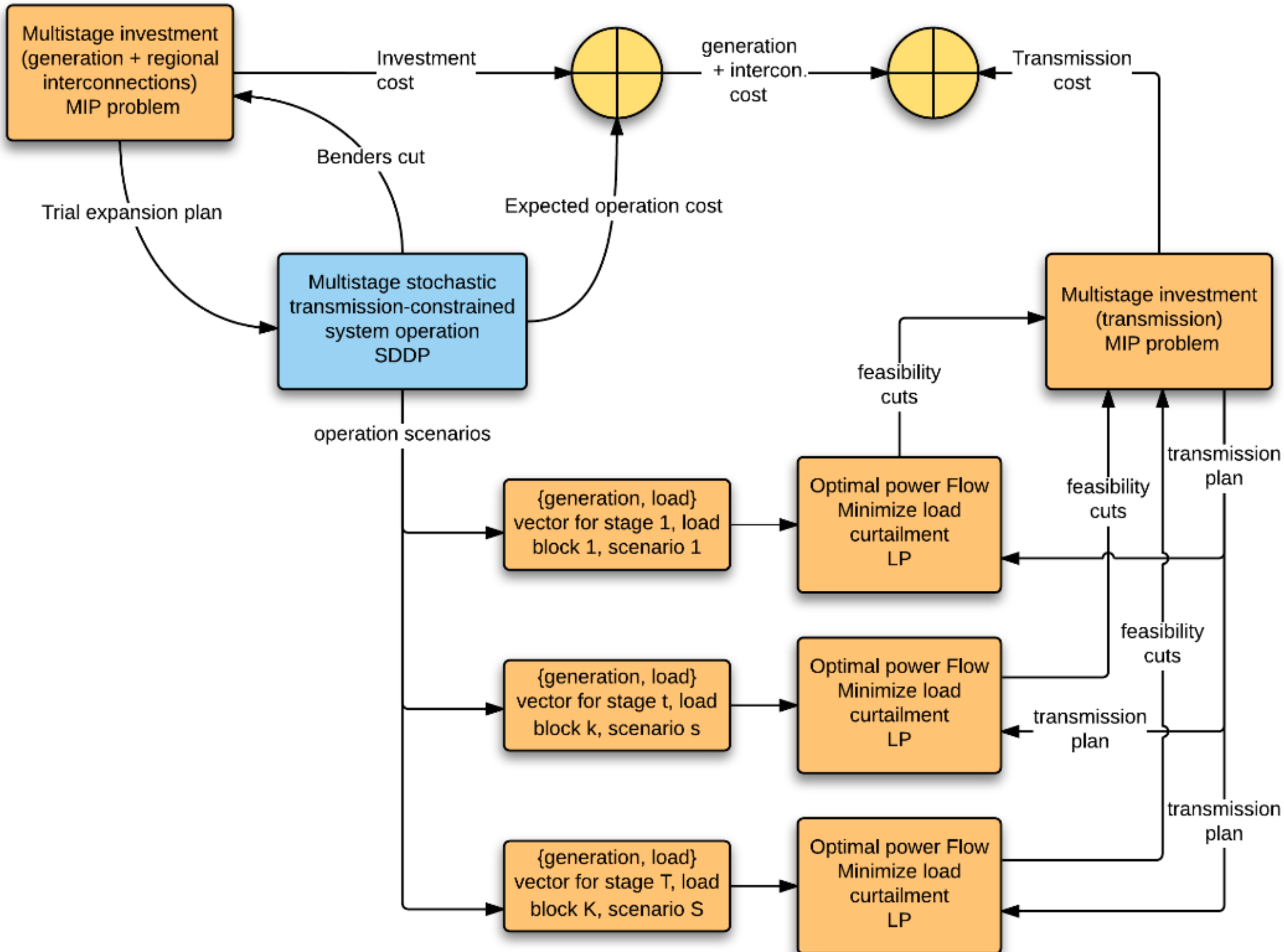


G&T Optimal Expansion Plan:

G: 9 TPPs, 7 HPPs, 3 Wind Farms

T: 12 Circuits (9 TLs and 3 Transf.)

Example 3: C. America Hierarchical G&T planning



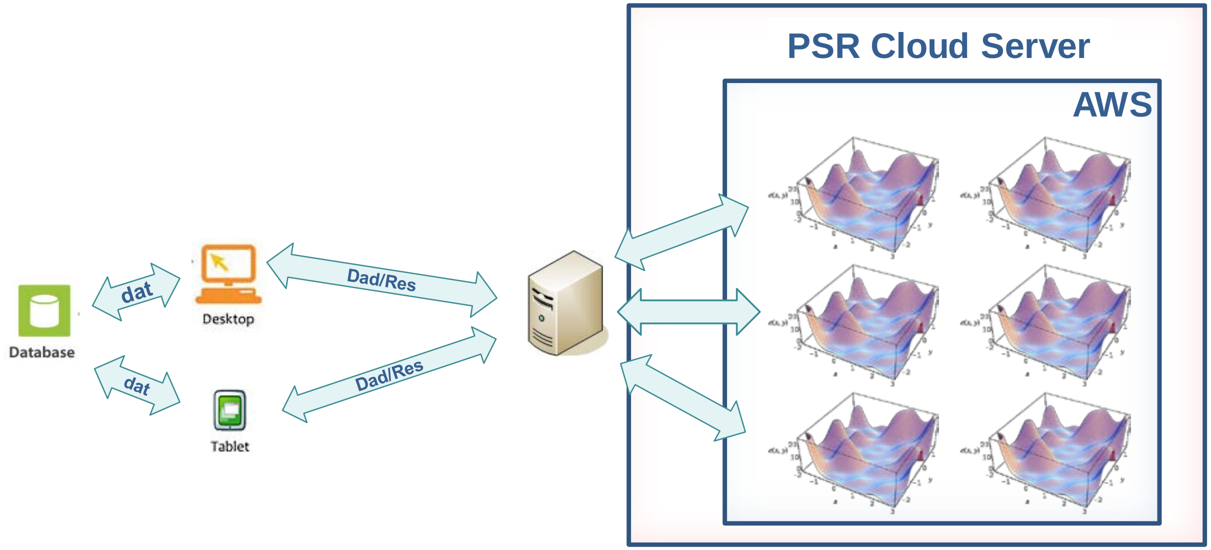
Hierarchical G&T Approach - Example: CA

Transmission System	
Num. of Buses:	**1980**
< 69 kV	1291
69 kV	283
115 kV	74
138 kV	151
230 kV	179
400 kV	2
Num of Circuits:	**2075**
Interconnections	13
Lines	920
Transformers	1142

MER transmission network visualization in PSR's PowerView Tool

After finding the Gen. Exp. Plan ➔ Optimal Trans. Exp. Plan

Transmission planning of each country in parallel



System	2019 plan (s)	2020 plan (s)	2021 plan (s)	2022 plan (s)	2023 plan (s)	2024 plan (s)
Costa Rica	99.48	1322.97	96.47	96.61	96.19	236.78
El Salvador	74.46	73.20	72.30	72.50	72.39	137.33
Guatemala	91.99	91.39	91.42	91.06	91.21	91.23
Honduras	178.61	84.90	221.16	84.69	84.65	218.94
Nicaragua	162.73	79.67	80.16	80.51	162.55	80.42
Panama	187.21	88.35	73.95	248.38	94.34	95.79

Conclusions

- 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 + Markov chains + scenarios can be used to represent uncertainties on inflows, renewable production, fuel costs, equipment availability and load
- The analytical ICF allows an efficient representation of multiple scale devices
- Parallel processing and, more recently, GPUs, are an essential component of the decomposition-based implementations

THANK YOU