

The Cost of Time-Inconsistent Long-Term Hydrothermal Operation Policies Induced by Short-Term Modeling Simplifications

Workshop ILAS 2019:

"Stochastic Programming models and algorithms for energy planning"

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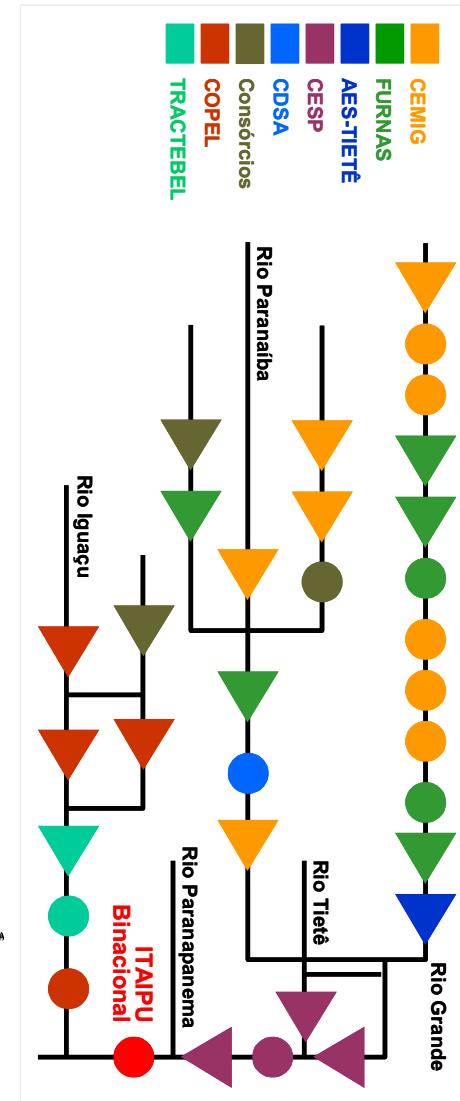
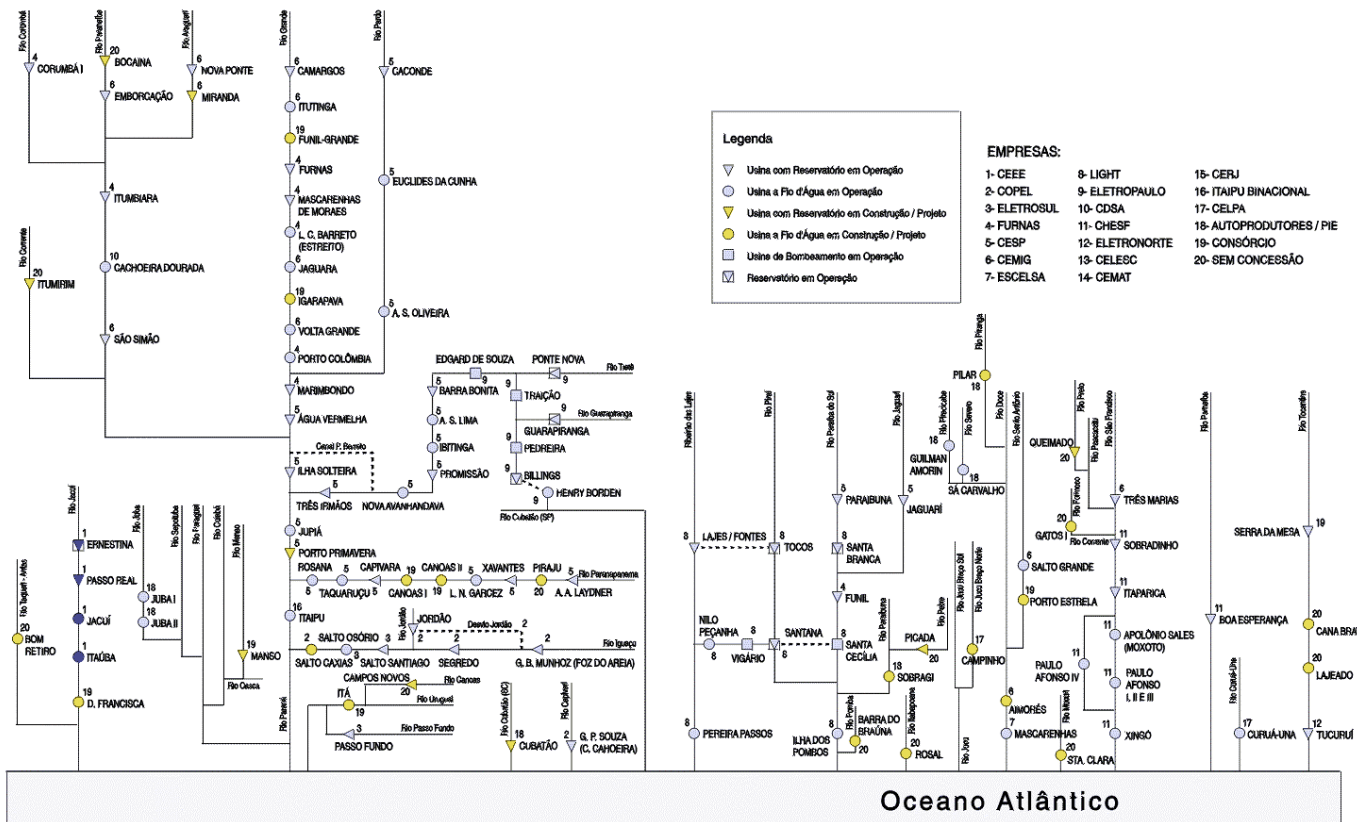
AGENDA

- Hydrothermal operation planning
- Time consistency
- Simplifications in planning models
- n-K security criterion dispatch
- Hybrid SDDP and CCG algorithm



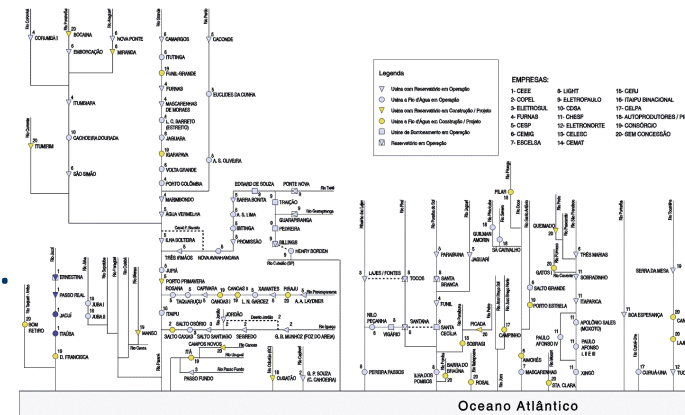
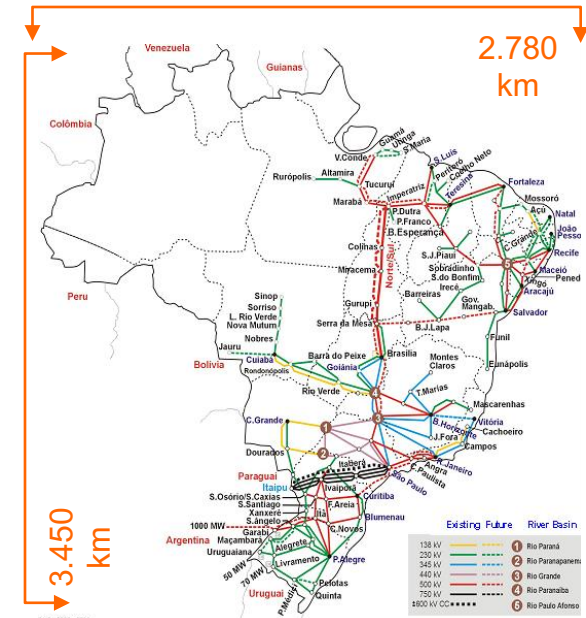
Brazilian power system case

- More than 10 river basins
- Wide variety of weather patterns
- Different ownerships in the same rivers



Challenge of operating a integrated hydrothermal system

- An ISO centrally dispatches the system “as a portfolio” to take advantage of the hydrological diversity,
- creating a hedge against dry periods and the waste of fossil fuel.
 - Transferring water from wet to dry basins
 - Transmission network
 - Transferring water from wet to dry periods
 - Large storage capacity
- The “water value” is calculated by an SDDP scheme.
- Spot prices “are” the system demand marginal



- Minimize the expected total thermal cost in a given time horizon
- Subject to
- Demand balance in each stage
- Water balance between stages
- Network constraints
- Bound constraints
- with uncertain inflows
 - w_t is \mathcal{F}_t – adapted
 - $\{\mathcal{F}_t\}_{t=1}^T$ is a filtration with the structure of how uncertainty is reveled through the time

$$\min_{g_t, y_t, f_t} \mathbb{E} \left[\sum_{t=1}^T \frac{c_t^T g_t}{(1+K)^t} \right]$$

Subject to

$$A_t g_t + P_t u_t + C_t f_t = d_t$$

$$v_t + u_t + s_t = v_{t-1} + w_t$$

$$(v_t, u_t, s_t, g_t, f_t) \in \mathcal{X}_t$$

$$(v_t, u_t, s_t, g_t, f_t) \text{ is } \mathcal{F}_t - \text{adapted}$$

- Dynamic equations

$$Q_t(v_{t-1}) = \min_{g_t, y_t, f_t} \mathbb{E}[c_t g_t + \beta Q_{t+1}(v_t)]$$

Sujeito a:

$$A_t g_t + P_t u_t + C_t f_t = d_t$$

$$v_t + u_t + s_t = v_{t-1} + w_{t,\omega}$$

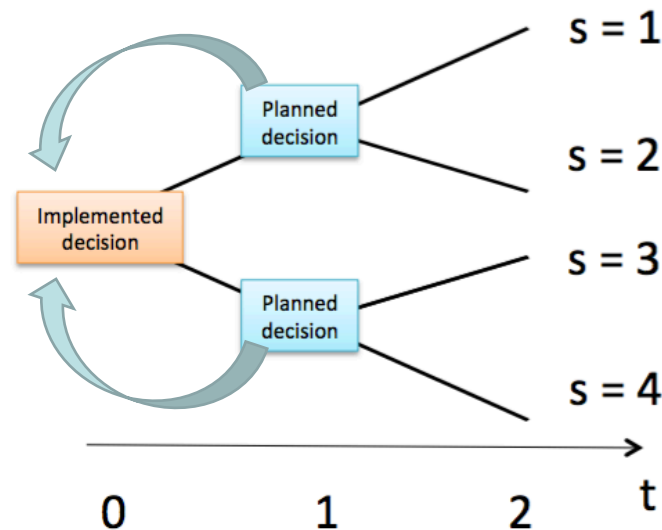
$$(v_t, u_t, s_t, g_t, f_t) \in \mathcal{X}_t$$

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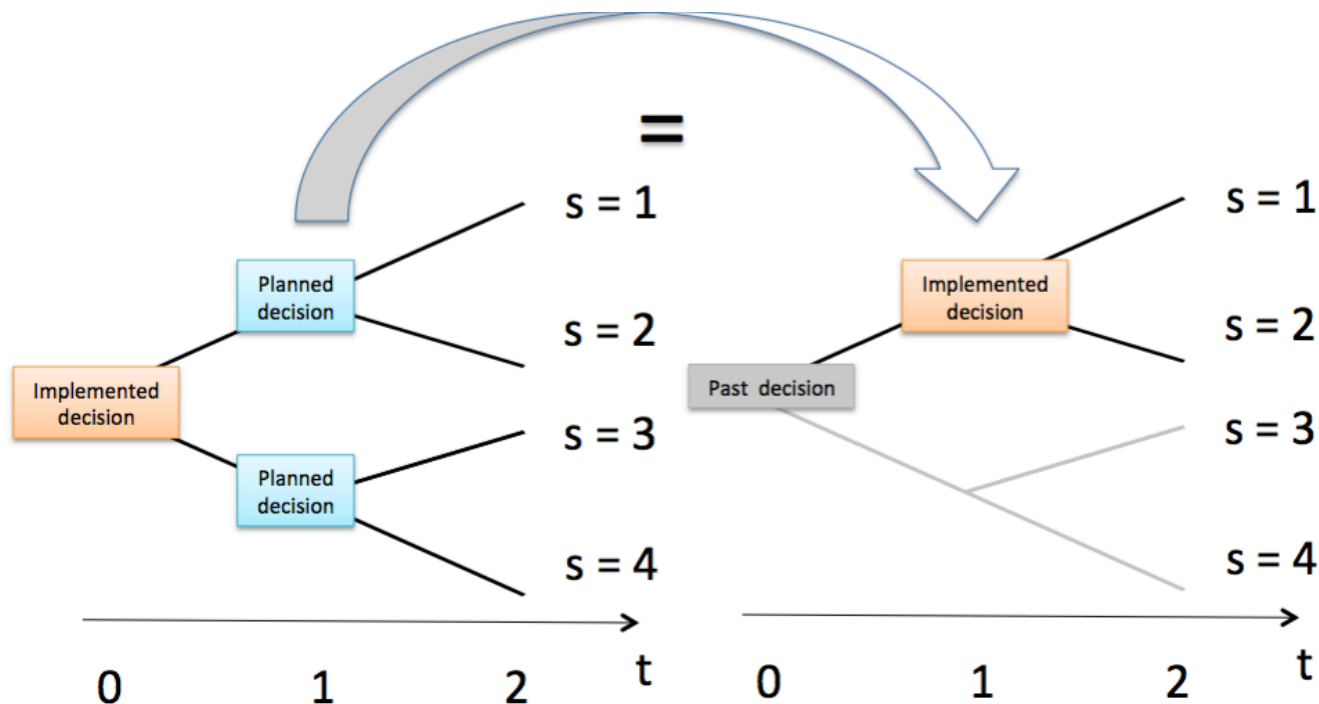


- To incorporate into first-stage decisions (those we actually implement) the flexibility that the dynamics of future decisions might bring
 - Implemented decisions: first-stage decisions of the conditioned multistage problem
 - Planned decisions: those used to model the dynamics of future decisions in the multistage problem



Time consistency definition

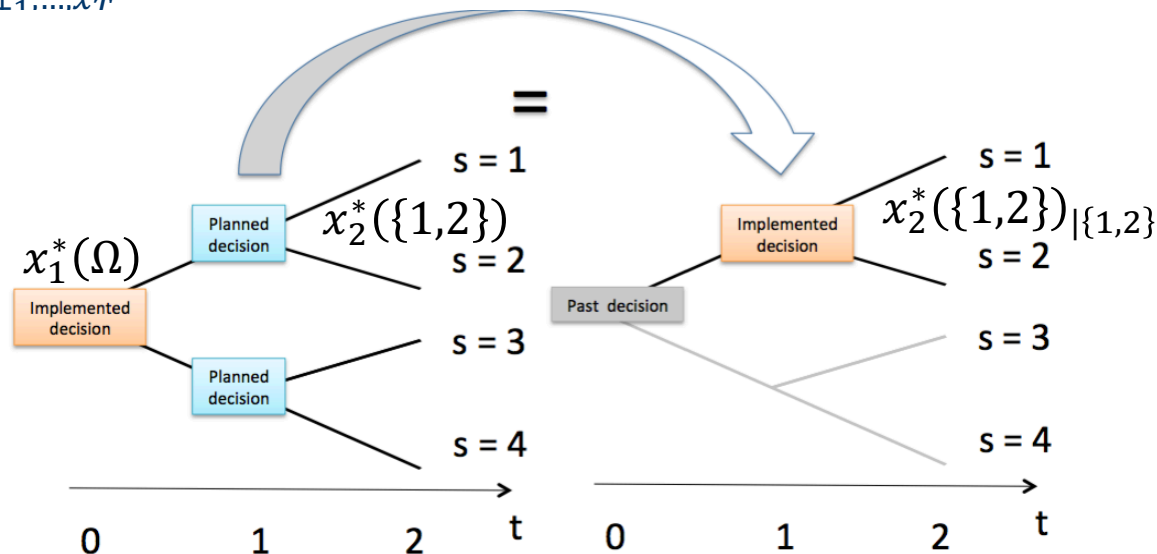
- A decision policy is time-consistent if future planned decisions are actually going to be implemented



B. Rudloff, A. Street, D. Valladão, "Time consistency and risk averse dynamic decision models: Definition, interpretation and practical consequences." European Journal of Operational Research (EJOR), 2014.

- A policy $\{(x_t^*: \Omega \rightarrow \mathbb{R}^n)\}_{t=1}^T$, devised in a given stage (e.g., $t=1$), is time consistent if its planned decisions are optimal with respect to the implementation model

$$\{x_t^*\}_{t=\tau}^T \in \arg \min_{x_{\tau+1}, \dots, x_T} \left\{ \rho_{\tau,T}[f(x_{\tau}, \xi_{\tau}), \dots, f_T(x_T, \xi_T)] \mid x_t \in \mathcal{X}_t(x_{t-1}, \xi_t), t = \tau + 1, \dots, T \right\}$$



A. Shapiro, A. Pichler, "Time and Dynamic Consistency of Risk Averse Stochastic Programs". Optimization On-line, 2016.

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How do we operate a real system?

- We devise an approximation for the system model, $\mathcal{X}_t^{plan} = \mathcal{X}^S$
- But in the short-term we implement decisions using a detailed version of the model, $\mathcal{X}_t^{imp} = \mathcal{X}^D$

$$\min_{g_t, y_t, f_t} c_t^T g_t + \beta Q_{t+1}^{plan}(v_t)$$

Sujeito a:

$$A_t g_t + P_t u_t + C_t f_t = d_t$$

$$v_t + u_t + s_t = v_{t-1} + w_{t,\omega}$$

$$(u_t, s_t, g_t, f_t) \in \mathcal{X}_t^{plan}$$

Planning model

(Generally simplified)

Model used to assess the cost-to-go function

$$\min_{g_t, y_t, f_t} c_t^T g_t + \beta Q_{t+1}^{plan}(v_t)$$

Sujeito a:

$$A_t g_t + P_t u_t + C_t f_t = d_t$$

$$v_t + u_t + s_t = v_{t-1} + w_{t,\omega}$$

$$(u_t, s_t, g_t, f_t) \in \mathcal{X}_t^{imp}$$

Implementation model

(Generally very accurate)

Model used to make the decision at stage t

- Planning policy: makes use of a planning model, $x_t^{plan} = x^S$

$$\left(x_\tau^{plan}, \{x_t^{plan}\}_{t=\tau+1}^T \right) \\ \in \arg \min_{\substack{x_\tau \\ x_{\tau+1}, \dots, x_T}} \left\{ \rho_{\tau,T}[f(x_\tau, \xi_\tau), \dots, f_T(x_T, \xi_T)] \middle| \begin{array}{l} x_\tau \in \mathcal{X}^S(x_{\tau-1}, \xi_\tau) \\ x_t \in \mathcal{X}^S(x_{t-1}, \xi_t), t = \tau + 1, \dots, T \end{array} \right\}$$

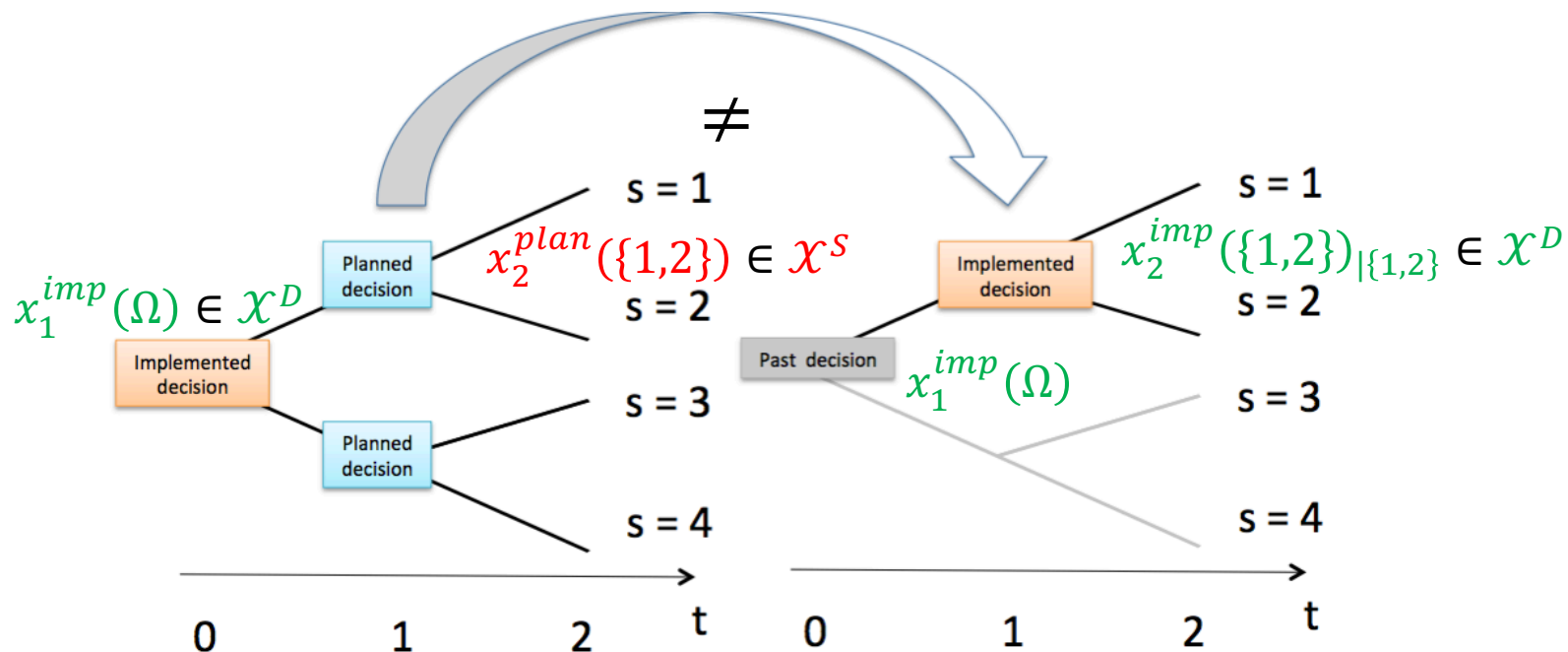
- Implementation policy: makes use of both implementation, $x_t^{imp} = x^D$, and planning model, $x_t^{plan} = x^S$

$$\left(x_\tau^{imp}, \{x_t^{plan}\}_{t=\tau+1}^T \right) \\ \in \arg \min_{\substack{x_\tau \\ x_{\tau+1}, \dots, x_T}} \left\{ \rho_{\tau,T}[f(x_\tau, \xi_\tau), \dots, f_T(x_T, \xi_T)] \middle| \begin{array}{l} x_\tau \in \mathcal{X}^D(x_{\tau-1}, \xi_\tau) \\ x_t \in \mathcal{X}^S(x_{t-1}, \xi_t), t = \tau + 1, \dots, T \end{array} \right\}$$

Implemented policy is time inconsistent

- $\{(x_t^{imp} : \Omega \rightarrow \mathbb{R}^n)\}_{t=1}^T$, adapted to $\{\mathcal{F}_t\}_{t=1}^T$, obtained for each τ with

$$(x_\tau^{imp}, \{x_t^{plan}\}_{t=\tau+1}^T) \in \arg \min_{x_\tau, x_{\tau+1}, \dots, x_T} \left\{ \rho_{\tau,T}[f(x_\tau, \xi_\tau), \dots, f_T(x_T, \xi_T)] \mid \begin{array}{l} x_\tau \in \mathcal{X}^D(x_{\tau-1}, \xi_\tau) \\ x_t \in \mathcal{X}^S(x_{t-1}, \xi_t), t = \tau+1, \dots, T \end{array} \right\}$$



The implemented rolling horizon hybrid policy is not optimal either for the simplified multistage model or for the detailed one

- Example: Two types of simplification
 - Network constraints (Voltage Kirchhoff law)

$$\mathcal{X}_t^{KVL} = \{(v_t, y_t, g_t, f_t) \in \mathcal{X}_t^{box} \mid f_t = R\theta_t\}.$$

- Security constraints (n-K security criterion)

$$\mathcal{X}_t^D(v_{t-1}, w_{t\omega}) = \left\{ (v_t, y_t, g_t, f_t) \in \mathcal{X}_t^{KVL} \mid \begin{array}{l} \exists (v_t^c, y_t^c, g_t^c, f_t^c) \in \mathcal{X}_{tc}^{KVL} : \\ A^c g_t^c + B^c y_t^c + C^c f_t^c = d_t; \forall c \in \mathcal{C} \\ v_t^c + H_t^c y_t^c = v_{t-1} + w_{t\omega} \quad \forall c \in \mathcal{C} \\ -R^{dn} \leq g_t^c - g_t \leq R^{up}; \forall c \in \mathcal{C} \end{array} \right\}.$$

- To measure the impact
 - A. Brigatto, A. Street, D. Valladão, "Assessing the Cost of Time-Inconsistent Operation Policies in Hydrothermal Power Systems." IEEE Transactions on Power Systems, 2017.

$$GAP = \frac{1}{M} \sum_{t=1}^T \sum_{\omega=1}^M c_t^\top g_{t,\omega}^{Imp} - \frac{1}{M} \sum_{t=1}^T \sum_{\omega=1}^M c_t^\top g_{t,\omega}^{Plan}$$

- Final forward simulation of both policies
- GAP is a measure to rank the impact of simplifications

Simplifications in KVL and n-1 security constraints

- Experiment where reality accounts for KVL and n-1 constraints
- planning stage disregards both

TABLE III
COST COMPARISON: INCONSISTENT VS PLANNING POLICIES (MMR\$).

	GAP	Planning policy	Inconsistent policy	Consistent policy
95% CI upper bound	3,890.89	3,407.20	7,165.59	3,675.77
Sample average	3,686.43	3,303.18	6,989.61	3,566.79
95% CI lower bound	3,481.99	3,199.15	6,813.63	3,457.80

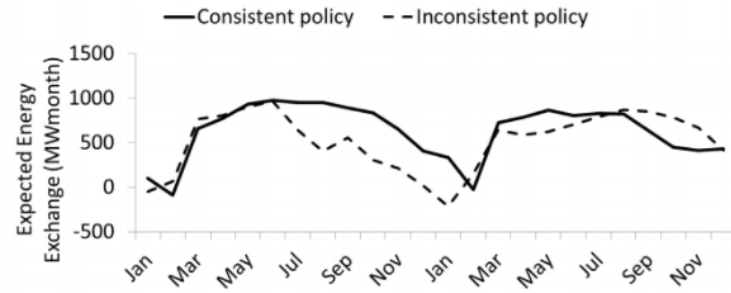
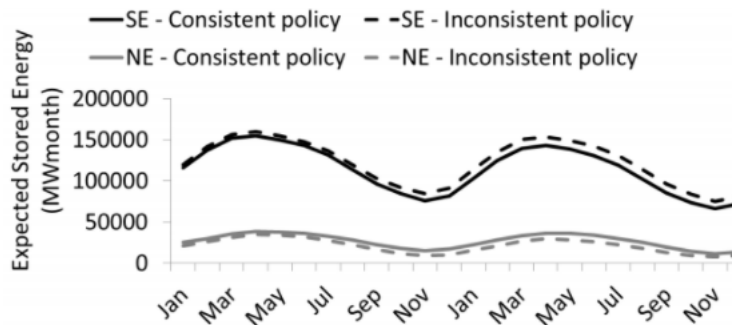


Fig. 9. Exchanged energy from the SE subsystem to the NE subsystem.



Fig. 10. Northeastern spot prices.

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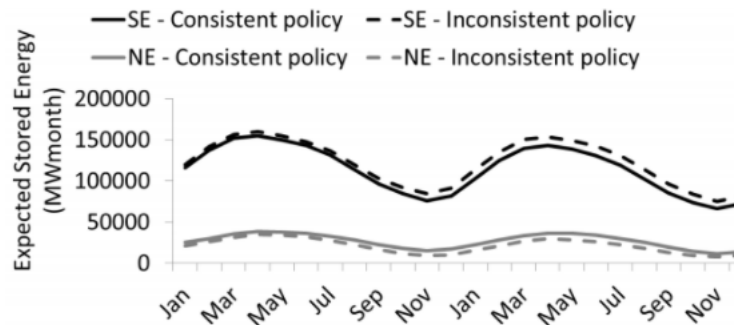


Fig. 8. Southeastern and Northeastern stored energy.

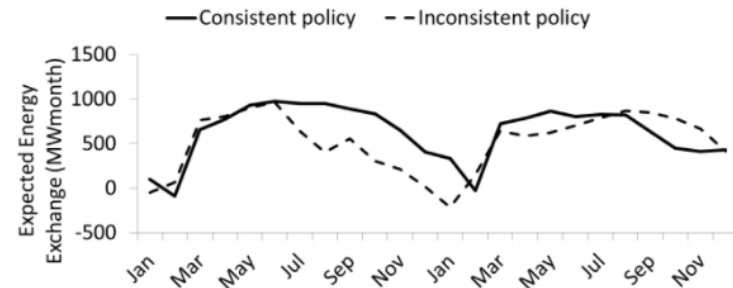


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Some final remarks for practical applications

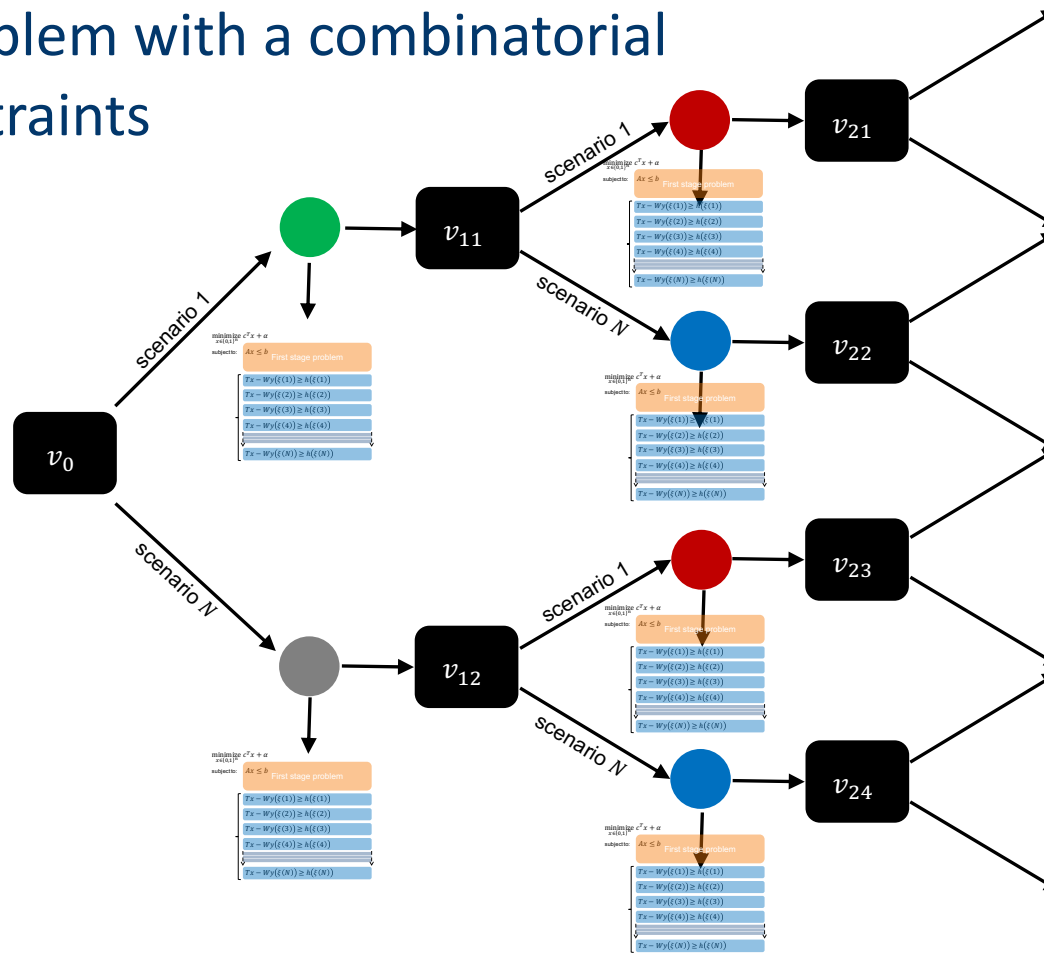
- Claim: In real life, we can try to manage or control time inconsistency, but we cannot avoid it completely
- Real-life decision processes are generally time inconsistent
- The fact that models generally produce time inconsistent policies is not an excuse to do not measure and try control it
 - Because small one-step ahead errors might produce huge cumulative deviations
- The time inconsistency GAP can be a monitoring measure
 - To rank simplifications
 - And to support the decision of enhancing the model

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At each stage in the SDDP we need to solve a problem with a combinatorial set of constraints

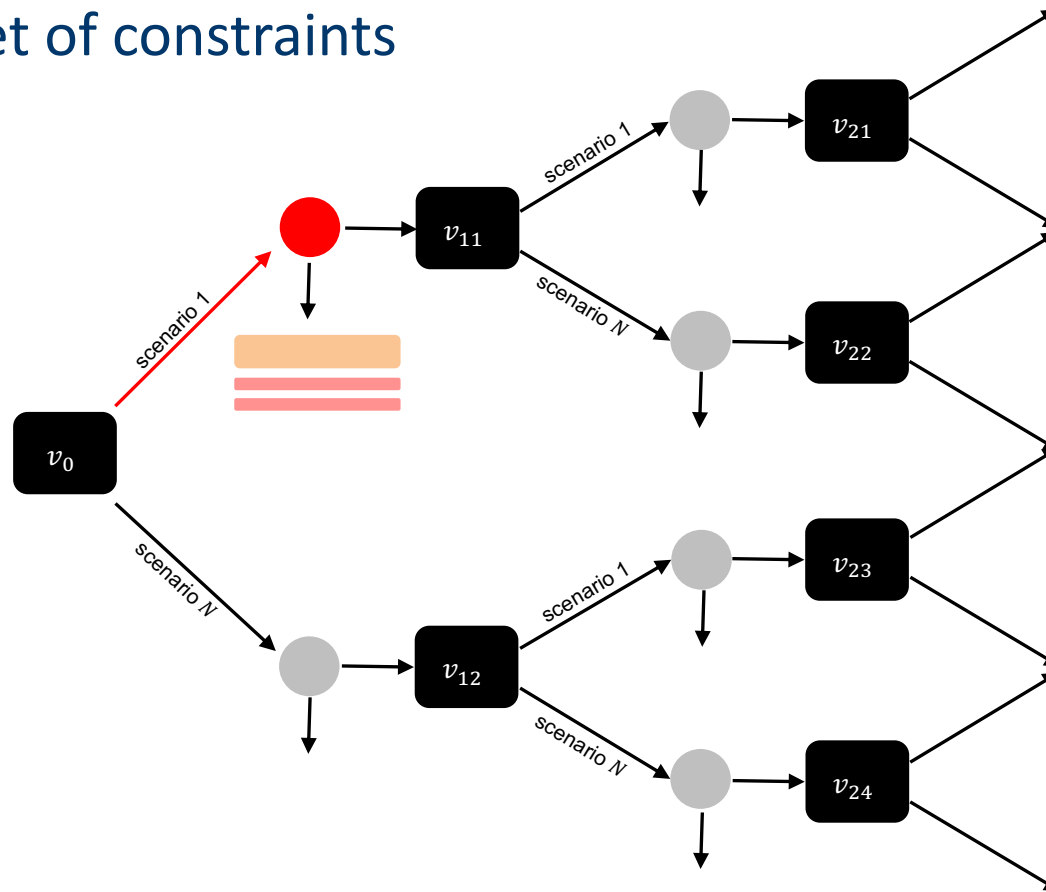


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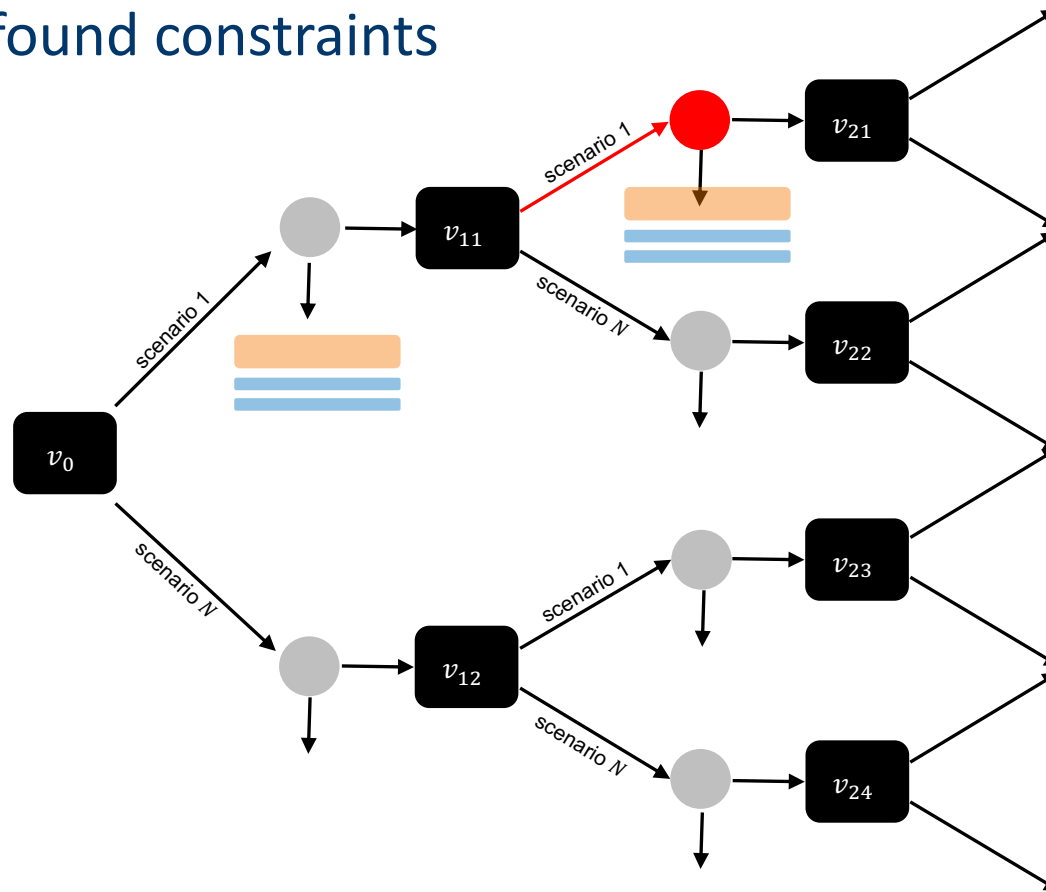
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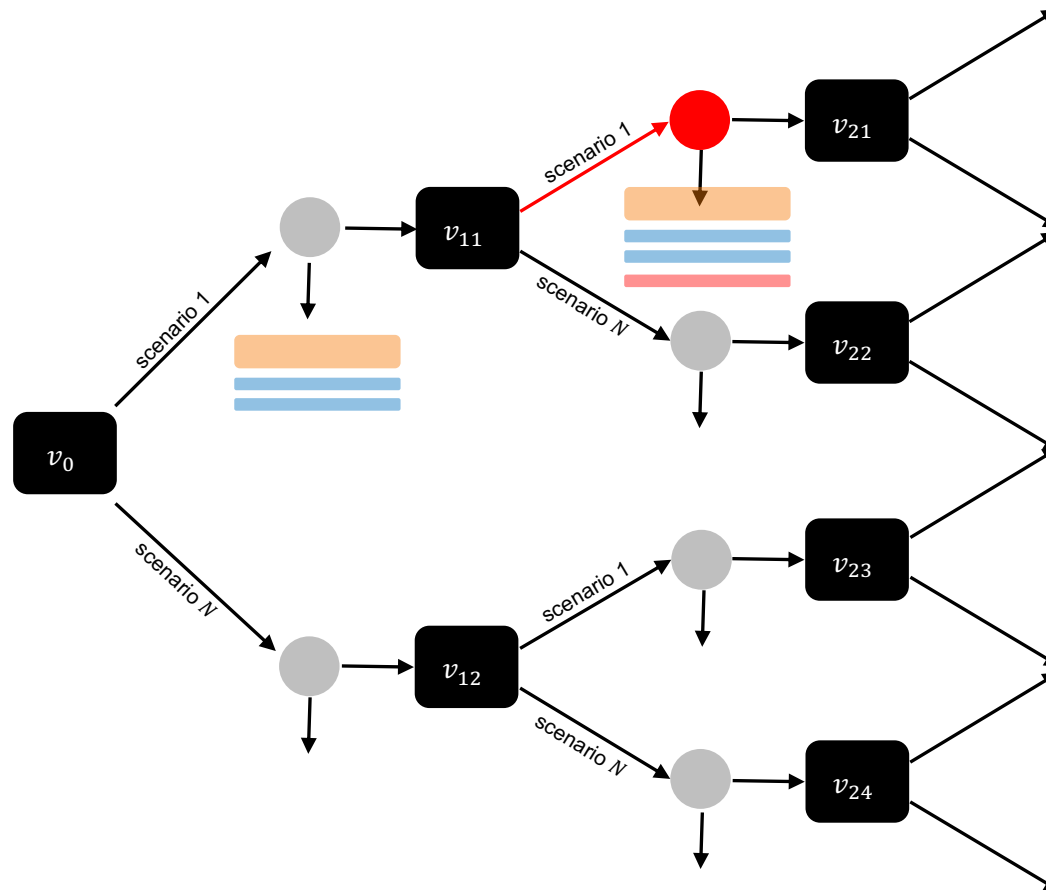
Solve the first problem and find the
umbrella set of constraints



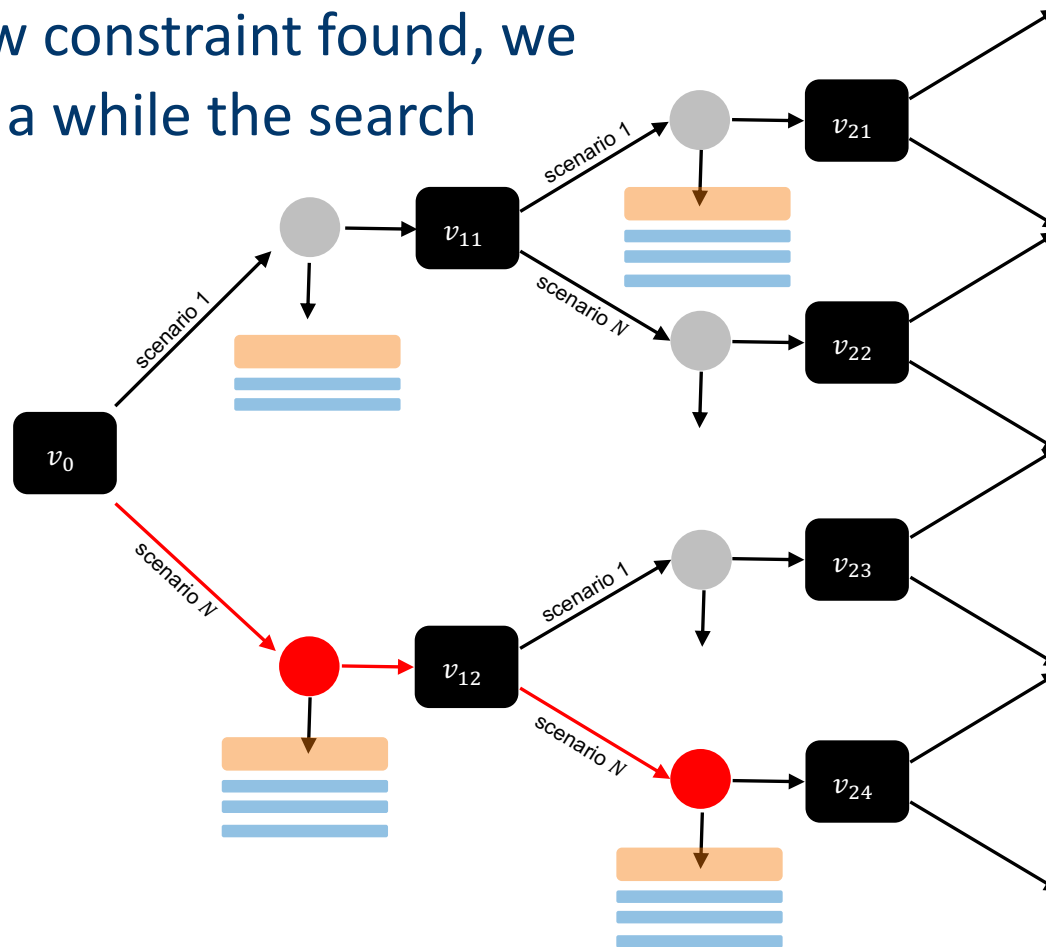
Second problem is initialized with previously found constraints



New violated constraints are added
if any



If a complete forward step finishes with no new constraint found, we turn off for a while the search



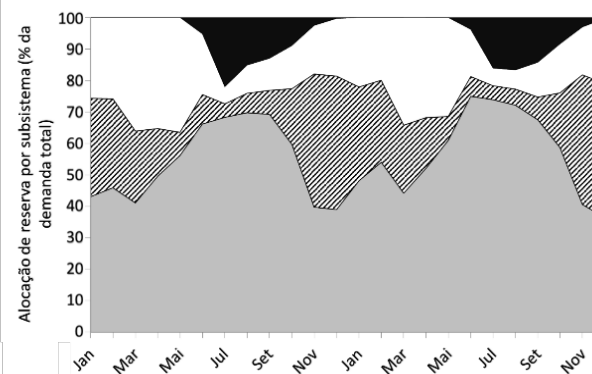
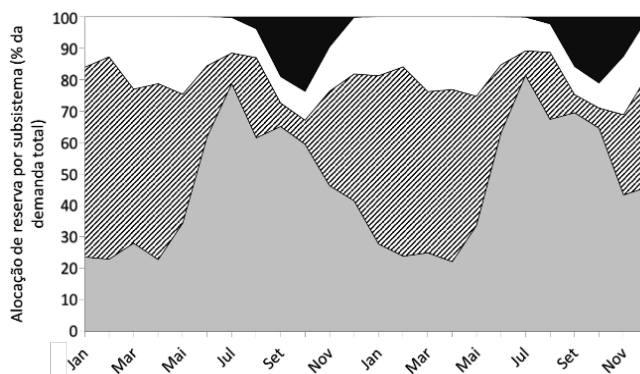
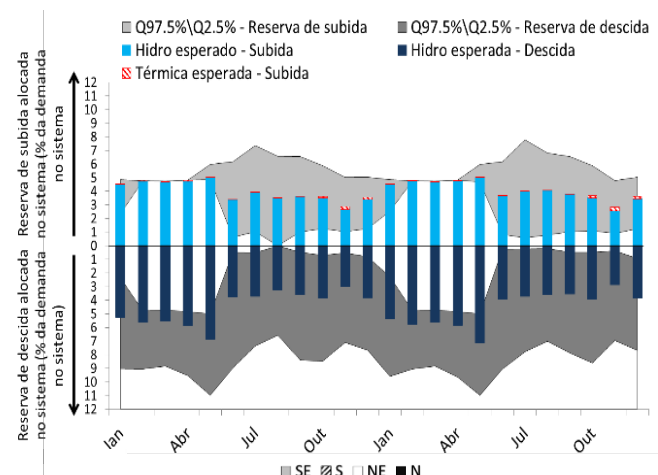
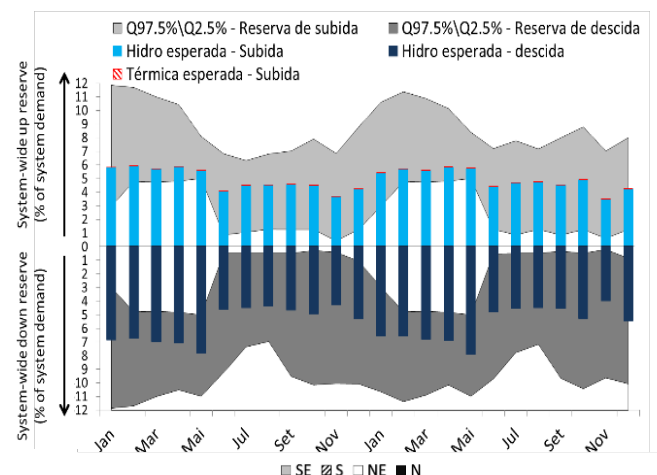
Results for the Brazilian System

Case	Running time (hours)			$ C^* $	$\frac{ C^* }{ C }$
	FCD	CCG _{MILP}	CCG _{INSP}		
$n - 0$	6.7	-	-	-	-
$n_T - 1$	22.9	13.8	12.5	3	30.0%
$n_{GT} - 1$	#	19.8	19.8	7	6.67%
$n_{GT} - 2$	#	27.0	53.6	12	0.22%

Case	Lower bound (z) (10^6 R\$)	Operational cost (\bar{z}) (10^6 R\$)			System-wide Up-reserves (% of total demand)			System-wide Down-reserves (% of total demand)		
		CI(95%) LB	Sample average	CI(95%) UB	$Q_{2.5\%}$	Sample average	$Q_{97.5\%}$	$Q_{2.5\%}$	Sample average	$Q_{2.5\%}$
$n - 0$	13,483.17	14,889.61	15,165.83	15,442.07	-	-	-	-	-	-
$n_T - 1$	13,729.48	15,570.95	15,850.17	16,129.40	0.82	0.95	1.06	0.82	0.96	1.07
$n_{GT} - 1$	13,868.83	15,707.45	15,988.48	16,269.51	0.91	1.18	1.51	0.83	0.97	1.11
$n_{GT} - 2$	18,463.96	21,600.69	21,924.60	22,248.52	3.51	4.00	4.44	3.78	4.45	5.17

Results for the Brazilian System

- A new n-K secure hydrothermal policy devised based on the GAP information
 - The reserves level are now part of the optimal policy



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Thanks you!
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- STREET, A.; BRIGATTO, A. C. ; VALLADAO, D. ; “Co-optimization of Energy and Ancillary Services for Hydrothermal Operation Planning Under a General Security Criterion.” IEEE Transactions on Power Systems, 2017
- BRIGATTO, A. C. ; STREET, A. ; VALLADAO, D. ; “Assessing the Cost of Time-Inconsistent Operation Policies in Hydrothermal Power Systems.” IEEE Transactions on Power Systems, 2017
- RUDLOFF, B. ; STREET, A. ; VALLADÃO, D. ; “Time consistency and risk averse dynamic decision models: Definition, interpretation and practical consequences.” European Journal of Operational Research (EJOR), 2014.