STOCHASTIC PROGRAMMING MODELS AND ALGORITHMS FOR ENERGY PLANNING





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### OUTLINE



- Stochastic programming/optimization tools for expansion and operation planning of the large-scale Brazilian system
- Challenge #1: Handling risk averse problems
- Challenge #2: Sampling backward SDDP scenarios
- Challenge (aspect) #3: Resampling forward SDDP scenarios
- Challenge #4: Trade-off between system Representation and quality of the results
- > Challenge #5: Performance requirements
- Challenge #6: Handling high uncertainty/variability of intermittent sources
- Bonus: Validation of DESSEM model for hourly prices in Brazil

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### Stochastic programming / optimization tools for expansion and operation planning of the large-scale Brazilian system

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### BRAZILIAN INTERCONNECTED SYSTEM (SIN)



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#### **GENERATION MIX - 2016 & 2021**



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## MAIN CHARACTERISTICS OF THE BRAZILIAN SYSTEM



- Large-scale system, predominantly hydro
- Stochastic inflows to reservoirs
- Long distances between generation sources and load
- Many hydro plants in cascade



#### **Coordinated operation is a VERY complex task!**

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### BRAZILIAN INTERCONNECTED SYSTEM (SIN) – HYDRO PLANTS



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#### HYDROTHERMAL PLANNING FOR THE **BRAZILIAN INTERCONNECTED SYSTEM**



**Developed by CEPEL**, collaborating with scientific comunity

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Validated in working groups in by ONS, CCEE, EPE, MME, ANEEL, as well as task forces with most power system utilities

**Approved for official** use by the regulatory energy

#### Used by:

- EPE to plan the system
- **ONS to dispatch plants**
- **CCEE** for market prices

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#### HYDROTHERMAL PLANNING FOR THE BRAZILIAN INTERCONNECTED SYSTEM



#### LONG, MID AND SHORT TERM GENERATION PLANNING



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### LONG TERM MODEL – NEWAVE Problem Formulation



#### MULTI-STAGE STOCHASTIC LINEAR PROGRAMMING PROBLEM



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### LONG TERM MODEL – NEWAVE Solving Strategy



#### **SDDP - STOCHASTIC DUAL DYNAMIC PROGRAMMING**



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#### **MID-TERM MODEL - DECOMP**

- Weekly steps for the 1<sup>st</sup> month
- > Monthly steps for the following months, with several water inflow scenarios
- Several load blocks for each time step
- > Coupling with long term model takes into account history of the system



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## Challenge #1:

### Handling risk-averse problems in large-scale systems

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**CVAR RISK MEASURE APPLIED TO SDDP (2013)** 



#### APPLICATION TO MULTISTAGE HYDROTHERMAL PLANNING

[Shapiro,10]

[Philpott, de Matos,12]



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#### **CVAR RISK MEASURE APPLIED TO SDDP (2013)**



#### DIRECT APPLICATION OF NESTED CVAR RISK-AVERSE CRITERION

#### **BACKWARD PASS**

- solve subproblems for all bacward scenarios ω
- ➢ identify the scenarios related to the α% highest stag values of  $z_{t,ω}$
- Build Benders cut with both expected value and risk averse terms

[Shapiro,Tekaya, Costa,Soares,12]

[Diniz, Tcheou, Maceira, 12]



**Backward scenarios** 

$$\begin{split} \varphi_{t}(\mathbf{x}_{t-1}) \geq & (1-\lambda) \sum_{\omega=1}^{K} p_{\omega} \left[ \mathbf{z}_{t,\omega^{*}} + (\pi_{t,\omega^{*}}, \mathbf{x}_{t-1} - \hat{\mathbf{x}}_{t-1,s}) \right] \\ & + & (\frac{\lambda}{\alpha}) \sum_{\omega \in \Omega_{\alpha}} p_{\omega} \left[ \mathbf{z}_{t,\omega^{*}} + (\pi_{t,\omega^{*}}, \mathbf{x}_{t-1} - \hat{\mathbf{x}}_{t-1,s}) \right] = \boxed{\mathbf{z}^{*} + \left\langle \overline{\pi^{*}}, \mathbf{x}_{t-1} - \hat{\mathbf{x}}_{t-1,s} \right\rangle} \end{split}$$

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### RISK AVERSER SURFACE – SAR (2013)



> Explicit protection against critical scenarios

[PSR,08]

[Diniz, Maceira, Vasconc., Penna,14]



#### SOME NOTES ON CHOOSING THE BEST POLICY IN RISK AVERSE PROBLEMS

- Yielding the least cost is not anymore a criterion to select the most suitable policy
- A multiciterion analysis has to be conducted making an out-ofthe sample assessment for different hydrological and system conditions of many aspects such as:

# Thermal generation costs X deficit risk (costs)

- Distribution of energy not served (ENS)
- Probability of spillage
- Evolution of the storage of the reservoirs



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## Challenge #2: Sampling backward SDDP scenarios

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## SOME NOTES ON BACKWARD SCENARIO GENERATION



- In sample average approximation (SAA) algorithms, usually a random (Monte Carlo) sampling is recommended to generate scenarios, in order to have more diversity
  - ✓ Many replications of the scneario tree should be performed
- However, the problem can only be solved ONCE
- The use of random sampling in backward scenarios makes the results very sensitive to the seed used to generate scenarios

Therefore, it is recommended to use clustering techniques when generating backward scenarios, even though the value of the optimal solution may be (a bit) biased

Also, while clustering, picking the centroid as representative of each cluster (instead of the closest object to the centroid) brings more stable results

### SCENARIO GENERATION: MONTE CARLO X CLUSTERING



#### **SELECTIVE SAMPLING (2009) MONTE CARLO** (K-MEANS) [Penna, Maceira, Damazio, 11] RD MEAN - Subsystem: 1 MEAN 45 56 67 45 56 67 78 89 100 111 Selective Sampling (SS) Current option RD S.D. - Subsystem: 1 RD S.D. - Subsystem: 1 S.D. 12 23 34 45 56 67 Periods 78 89 100 111 34 45 56 67 78 89 100 111 Periods 23 Selective Sampling (SS) Current option

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### SCENARIO GENERATION: MONTE CARLO X CLUSTERING



#### Lower bound for the optimal solution

10 different samples



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## Challenge (aspect) #3: Resampling Forward SDDP scenarios

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#### FORWARD RESAMPLING



#### > OBJECTIVE: To allow a more representative part of the HUGE multi-stage scenario tree to be visited



# SDDP convergence has been proved once forward resampiling is performed

 Philpott e Guan [2007] - On the convergence of stochastic dual dynamic programming and related methods. Operation Research Letters 36 (4) – 450-455

#### RESAMPLING - RESULTS FOR DIFFERENT SEEDS (1/2)



#### LOWER BOUND FOR EACH SEED



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The main objective of NEWAVE model is NOT TO SOLVE THE **DISCRETE MATHEMATICAL PROBLEM**, but rather to **OBTAIN AN OPERATION POLICY** for the **CONTINUOUS PROBLEM** 



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The main objective of NEWAVE model is NOT TO SOLVE THE DISCRETE MATHEMATICAL PROBLEM, but rather to OBTAIN AN OPERATION POLICY for the CONTINUOUS PROBLEM



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The main objective of NEWAVE model is NOT TO SOLVE THE DISCRETE MATHEMATICAL PROBLEM, but rather to OBTAIN AN OPERATION POLICY for the CONTINUOUS PROBLEM



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The main objective of NEWAVE model is NOT TO SOLVE THE DISCRETE MATHEMATICAL PROBLEM, but rather to OBTAIN AN OPERATION POLICY for the CONTINUOUS PROBLEM





#### Which one is the best policy for t=1?



exact FCF for t=1 of the *mathematical* problem (depends on green scenarios in t=2)

Approximation of the FCF if forward samples are taken from the continuous distribution

Approximation of the FCF if forward samples are taken from backward scenarios (much smaller number of visited states)

- The red points are enough to find the optimal solution for the mathematical problem (red + green scenarios)
- However, we know this is NOT the true problem: we should be prepared for the "real" continuous distribution
- So, why do we use a discrete backward distribution?
  - ✓ we must set a tractable and exact mathematical problem



# The main objective of NEWAVE model is not to solve the problem, but rather to obtain an operation policy

- With such policy it is possible to simulate a large number of scenarios in order to obtain proper statistics for system operation:
  - ✓ Average System Marginal costs
  - ✓ Average thermal generation
  - ✓ Average storage in the reservoirs along time
  - ✓ Deficit risk and average load curtailment
  - ✓ Average spillage

The policy should be "good" for ANY SET OF SCENARIOS IN THE CONTINUOUS DISTRIBUTION of the random variable

Therefore, for practical applications, we **sample the forward scenarios from the continuous distribution**, rather than the set of backward noises, even though this is a theoretical requirement to find the optimal solution of the mathematical problem (**our aim is NOT to find it!!**)



### **Challenge #4:**

### Trade-off between system Representation and quality of the results

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#### MODELING OF EQUIVALENT RESERVOIRS IN THE LONG TERM



Individual aspects are modeled as much as possible

- Loss of efficieny with the water head
- ✓ Inflows/spillage in run of the river plants, etc.

[Arvanitidis, Rosing,70]

[Maceira,Duarte, Penna,Tcheou,11]

[Terry,Maceira, Mercio,Duarte,04]



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#### INCREASE IN THE REPRESENTATION OF THE HYDRO SYSTEM ALONG TIME

- The main goal is to capture diversity of the hydrological behaviour, while still keeping a lower state space
- Due to market aspects, the number of market areas is kept

[de Matos, Finardi, Silva, 08]

Maceira, Diniz, Vasconcellos,11]

[Ennes, Penna,

- The increase in the number of EERs is based on comprehensive studies performed by CPAMP (ONS,CCEE,EPE,MME,ANEEL,CEPEL)
  - ✓ until 2015: 4 EERs
  - ✓ 2016: **9 EERs**
  - ✓ 2018: **12 EERs**
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#### HYBRID INDIVIDUAL / EER REPRESENTATION IN NEWAVE



- Allows NEWAVE model to represent the hydropower plants individually in the entire or in part of its planning horizon
- Takes advantage of both modellings, without increasing too much the computational effort by considering:
  - the benefits of an individual representation of HPPs in the horizon closer to the operational decision making
  - as many EERs as necessary to represent the hydrological diversity among the river basins, in the later stages



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## SOME NOTES ON SYSTEM REPRESENTATON



- From the system modeling point of view, the consideration of individual reservoirs in SDDP itself is not a challenge
  - Constraints are similar (and simpler) than mid/short term models, and the construction of Benders cut in DDP or SDDP is similar
- Modeling of random variables (e.g. past inflows) for individual plants is more involving, due to its high dimensionality and the statistical model (overparametrization, spatial/serial correlations...)

One major aspect is the trade-off between system representation and the quality of the results

- ✓ It is not enough to simply run a number of SDDP iterations: it is VERY important to make sensitivity analysis on the final simulation results
- A critical issue is the quality and impact of the detailed data related to system components and constraints in the long term
  - It is not possible to satisfy all constraints in all future scenarios: in practice, some constraints are adjusted according to the system state, and one cannot simply discard violated scenarios
  - ✓ Aggregate constraints may be more effective in the long run



## Challenge #5: Performance Requirements

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### COMPUTATIONAL EFFICIENCY AND QUALITY OF THE RESULTS





# Reproducibility of the results

The results should be identical regardless of the machine and number of parallel processors

# Solving strategy for economic dispatch subproblems

- warm starts
- > optimal simplex basis recovery (LPs)
- dynamic piecewise linear models
- [Diniz,Ennes, Cabral,12]

cut selection

- [Matos, Philpott, Finardi,13]
- MIP: Local branching [Fischetti, Lodi,03]

[Saboia,Lucena,11]

#### **Strict validation process**

- CPAMP committee
- Task forces for each model
- > + 300 users



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## Challenge #6:

## Handling high uncertainty/variability of intermittent sources

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#### MODELING OF RENEWABLE GENERATION – SHORT TERM

- Intermittent renewabel generation turns the traditional deterministic unit commitment model into a stochastic unit commitment model
  - wind generation has to be represented as interruptible generation, for feasible AND economic reasons
  - reliable models for scenario generation of wind production should be developed

[Pessanha et al,18]



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[Cotia, Borges, Diniz, 19]

### MODELING OF RENEWABLE GENERATION – LONG TERM

#### "SOFT LINK"

integration between long term and short term models [Deane, Chiodi, Gargiulo, 12]



#### "HARD LINK"

In directly represent hourly operation constraints in the long term model [Deane, Chiodi, [Pina, Silva, [Tejada-arango Gargiulo, 12] Ferrão, 13] Domeshek, Wogrin 18]

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### This list of challenges is BY FAR not exhaustive:

- > How to make SDDiP practical?
- How to better handle long tem uncertainties? (e.g. load growth)
- How to better address short range uncertainties on intermittent generation?
- Consideration of climate changes
- > etc, etc, etc.

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[Arroyo, Conejo, 04]	Arroyo, J.M., Conejo, A.J., "Modeling of start-up and shut-down power trajectories of thermal units", IEEE Transactions on Power Systems, v.19, n. 3, pp 1562-1568, Aug. 2004.
[Birge,85]	J.R. Birge, "Decomposition and partitioning methods for multistage stochastic linear programs", Operations Research, v.33, n.5, pp. 989-1007, 1985.
[Birge, Louveaux,97]	J. R. Birge, F. Louveaux, "Introduction to stochastic programming", Springer series in OR, 1997.
[Carrion, Arroyo,06]	M. Carrion, J. M. Arroyo, "A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem", IEEE Transactions on Power Systems, v. 21, n. 3, pp. 1371-1378, Aug. 2006.
[Cotia, Borges, Diniz, 19]	B.P. Cotia, C. L.T. Borges, A.L. Diniz, "Optimization of wind power generation to minimize operation costs in the daily scheduling of hydrothermal systems", Int. J. Elect. Power and Energy Syst. v.113, p. 539-548, 2019
[Dam, Kucuk, Rajan, Atam, 13]	P. Damci-Kurt, S. Kucukyavuz, D. Rajan, and A. Atamturk, A Polyhedral Study of Ramping in Unit Committment, Univ. of California-Berkeley, Res. Rep. BCOL.13.02 IEOR, Oct. 2013 Available: http://ieor.berkeley.edu/atamturk/pubs/ramping.pdf
[Deane, Chiodi, Gargiulo, 12]	J. Deane, A. Chiodi, MGargiulo, et al. "Soft-linking of a power systems model to an energy systems model", Energy, v. 42, n. 1, pp. 303–312, 2012.

[Diniz,Costa, A. L. Diniz, F. S. Costa, M. E. P. Maceira, T. N. Santos, L. C. Brandão, R. N. Cabral, Maceira, Santos, "Short/Mid-Term Hydrothermal Dispatch and Spot Pricing for Large-Scale Systems -Brandao,Cabral,18] the Case of Brazil", 20th Power Systems Computation Conf., Ireland, June 2018.



[Diniz, Maceira,08]	A.L. Diniz, M.E.P. Maceira, , "A four-dimensional model of hydro generation for the short-term hydrothermal dispatch problem considering head and spillage effects", IEEE Trans. Power Syst., v. 23, n.3, pp. 1298-1308,2008.
[Diniz, Santos, Saboia, Maceira,18]	A. L. Diniz, T.N.Santos, C.H. Saboia, M.E.P. Maceira,"Network constrained hydrothermal unit commitment problem for hourly dispatch and price setting in Brazil: the DESSEM model', 6th Int. Workshop on Hydro Scheduling in Competitive Electricity Markets, Norway,2018.
[Diniz,Sousa, Maceira et al,02]	A. L. Diniz, L. C. F. Sousa, M. E. P. Maceira, S. P. Romero, F. S. Costa, C. A. Sagastizabal, A. Belloni, "Estratégia de representação DC da rede elétrica no modelo de despacho da operação energética – DESSEM", VIII SEPOPE,2002.
[Diniz, Souza,14]	A. L. Diniz, T. M. Souza, "Short-Term Hydrothermal Dispatch With River-Level and Routing Constraints", IEEE Trans. Power Systems, v.29, n.5, p. 2427–2435, 2014.
[Diniz, Tcheou, Maceira,12]	A. L. Diniz, M. P. Tcheou, M. E. P. Maceira, "Uma abordagem direta para consideração do CVAR no problema de planejamento da operação hidrotérmica" XII SEPOPE - Symposium of Specialists in Electric Operational and Expansion Planning,2012
[Fischetti, Lodi, 03]	M. Fischetti, m".Lodi, "Local Branching", Mathematical Programming Series B, v.98, pp. 23-47, 2003
[Kall,	P. Kall, J. Mayer, "Stochastic linear programming: models, theory and

Mayer,10] computation", John Wiley & Sons, 2ed,2010



[Liu,Shahidehpour, Li,Mahmoud,09]	C. Liu, M. Shahidehpour, Z. Li, M. Fotuhi-Firuzabad, "Component and Mode Models for the short term scheduling of Combined Cycle Units" IEEE Trans. Power Syst., vol. 24, no. 2, pp. 976-990, May 2009.			
[Maceira,93]	M.E.P Maceira, "Programação Dinâmica Dual Estocástica Aplicada ao Planejamento da Operação Energética de Sistemas Hidrotérmicos com Representação do Processo Estocástico de Afluências por Modelos Auto-Regressivos Periódicos", Rel. Técnico CEPEL 237/93, 1993.			
[Maceira,Duarte, Penna,Mor, Melo,08]	M.E.P. Maceira, V.S. Duarte, D.D.J. Penna, L.A.M. Moraes, A.C.G. Melo, "Ten years of application of stochastic dual dynamic Programming in official and agent studies in Brazil – Description of the NEWAVE program", 16th PSCC Conf. , Glasgow, July 2008.			
[Maceira,Penna, Diniz,Pinto,Melo, Vasconc.,Cruz,18] M.E.P. Maceira, D.D.J. Penna, A.L. Diniz, R.J. Pinto, A.C.G. Melo, C.V. Vasconc C.B. Cruz, "Twenty Years of Application of Stochastic Dual Dynamic Program Official and Agent Studies in Brazil – Main Features and Improvements on NEWAVE Model", Power Syst. Computation Conference (PSCC), Dublin, Ju				
[Maceira, Terry, Costa et al, 02]	M.E.P. Maceira, L.A. Terry, F.S. Costa, J. M. Damazio, A C. G. Melo, "Chain of optimization models for setting the energy dispatch and spot price in the Brazilian system", Proceedings of the Power System Computation Conference – PSCC,2002.			
[Morales-Espana, Latorre, Ramos, 13]	G. Morales-Espana, J. M. Latorre, and A. Ramos, "Tight and compact MILP formulation of start-up and shut-down ramping in unit commitment," IEEE Trans. Power Syst., vol. 28, no. 2, pp. 1288–1296, May 2013.			
[Morales-Espana, Correa-Posada, Ramod,16]	G. Morales-Espana, C,M. Correa-Posada and A. Ramos, "Tight and compact MILP formulation of Configuration-Based Combined-Cycle Units," IEEE Trans. Power Syst., vol. 31, no. 2, pp. 1350–1359, March 2016.			

J. Ostrowski, M. Anjos, and A. Vannelli, "Tight mixed integer linear programming [Ostrowsku, formulations for the unit commitment problem," IEEE Trans. Power Syst., vol. 27, Anjos, Vanneli, 13 no. 1, pp. 39-46, Feb. 2012. [Pereira, M. V. F. Pereira, L. M. V. G. Pinto, "Multi-stage stochastic optimization applied to Pinto,91] energy planning", Mathematical Programming, v. 52, n.1-3, pp. 359-375, May 1991. [Pina, Silva, A. Pina, C. A. Silav, P. Ferrão, "High-resolution modeling framework for planning Ferrão, 13] electricity systems with high penetration of renewables", Applied Energy, v. 112, pp. 215-223, 2013. C. H. Saboia, A. Lucena, "A column generation approach for solving very large [Saboia, scale instances of the brazilian long term power expansion planning model, Lucena,11] 17th PSCC - Power Syst. Comp. Conf., Stockholm, Sweden, Aug. 2011. [Saboia, C. H. M. de Saboia, A. L. Diniz, "A local branching approach for network-**Diniz,16**] constrained thermal unit commitment problem under uncertainty", 19th Power Systems Computation Conference (PSCC), Genoa, Italy, Jun. 2016. [Santos, T. N. Santos, A. L. Diniz, "A Dynamic Piecewise Linear Model for DC Transmission **Diniz**, **11**] Losses in Optimal Scheduling Problems", IEEE Transactions on Power Systems, v.26, n.2, pp. 508-519, May 2011. A. Shapiro, W. Tekaya, J.P. Costa, M.P. Soares, "Risk neutral and risk averse [Shapiro,Tekaya, Stochastic Dual Dynamic Programming method", European journal of operational Costa, Soares, 12] research, v. 224, n.2, pp. 0375-0391, Jan. 2013

[Stott, B. Stott, J. L. Marinho, "Linear programming for power-system network security Marinho, 79 applications", IEEE Trans. Power Apparatus and Systems, v. 98, n.3, pp. 837-848, 1979.

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- [Wogrin, Dueñas, Delgadillo, 14] S. Wogrin, P. Dueñas, A. Delgadillo, "A new approach to model load levels in electric power systems with high renewable penetration", IEEE Trans. Power Syst. v. 29, n. 5, pp. 2210–2218, 2014
- [Tejada-arango D. A., Tejada-arango, M. Domeshek, S. Wogrin, et al. "Enhanced representative days Domeshek, and system states modeling for energy storage investment analysis", IEEE Trans.
  Wogrin 18] Power Syst, v. 33, n. 6, pp. 6534–6544, 2018.

[Poncelet, K. Poncelet, H. Höschle, E. Delarue, "Selecting representative days for capturing the implications of integrating intermittent renewables in generation expansion planning problems", IEEE Trans. Power Syst, v. 32, n. 3, pp. 1936–1948, 2017.

## **OBRIGADO!**

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> Hourly prices with DESSEM model



Ministério de Minas e Energia



## Validation of DESSEM model for hourly prices in Brazil

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### DETAILED SYSTEM REPRESENTATION



#### **DETAILED REPRESENTATION OF THE ELECTRICAL NETWORK**



optimization tools for the energy planning of real systems

### HYDRO PLANTS PRODUCTION FUNCTION



#### VARIATION OF EFFICIENCY WITH THE WATER HEAD

#### $GH_i = 9.81 \times 10^{-3} \,\eta Q \left[ h_{up}(V) - h_{dn}(Q+S) - h_{loss} \right]$





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#### **HYDRO CONSTRAINTS**





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#### **RIVER ROUTING**

Representation of water propagation curves along the river courses

[Diniz,Souza,14]

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### NONCONVEX THERMAL UNIT COMMITMENT CONSTRAINTS (1/2)

#### Minimum generation (once ON)

$$0 \qquad \frac{gt_i}{gt_i} \qquad 1 \qquad \frac{gt_i}{gt_i} u_i^t \le gt_i^t \le \overline{gt_i} \cdot u_i^t$$

#### Startup/shutdown costs



$$Cs_i\left(u_i^{t-1}-u_i^t\right) \leq S_i^t$$

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#### Minimum up/down times



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#### **NONCONVEX THERMAL UNIT COMMITMENT CONSTRAINTS (2/2)**

[Arroyo, Conejo, 04] Start-up / Shutdown trajectories

 $GT_i^t \geq \underline{GT}_i \left( u_i^t - \sum_{k=1}^{NU_i} \hat{y}_i^{t-k+1} - \sum_{k=1}^{ND_i} \tilde{y}_i^{t+k-1} \right) +$  $\sum_{\substack{k=1\\ND_i\\k=1}}^{NU_i} TrUp_i(k) \cdot \hat{y}_i^{t-k+1} + \sum_{\substack{ND_i\\k=1}}^{ND_i} TrDn_i(ND_i - k + 1) \cdot \tilde{y}_i^{t+k-1}$  $GT_i^t \leq \overline{GT}_i \left( u_i^t - \sum^{NU_i} \hat{y}_i^{t-k+1} - \sum^{ND_i} \tilde{y}_i^{t+k-1} \right) +$ 

$$\sum_{k=1}^{NU_{i}} TrUp_{i}(k) \cdot \hat{y}_{i}^{t-k+1} + \sum_{k=1}^{ND_{i}} TrDn_{i}(ND_{i}-k+1) \cdot \tilde{y}_{i}^{t+k-1}$$

 $gt_i$  $gt_i$ 9 1 0 15 16 17 18 19 20 21 22 23 24 25 26 27 28 Status  $(u^t) = 0 \quad 0$ 1 1 1 1 1 1 1 1 1 0 0 0 0

TOn = 22

Auxiliary variables:

$$\widetilde{y}_i^t = \widetilde{w}_i^t + \left(u_i^{t-1} - u_i^t\right)$$

 $\widetilde{y}_i^t + \widetilde{w}_i^t \leq 1$ 

 $NU_i$ : length of startup trajectory

 $ND_i$ : length of shutdown trajectory

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$$\widetilde{v}_i^t = \widetilde{w}_i^t + \left(u_i^{t-1} - u_i^t\right)$$

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# $\begin{bmatrix} \kappa \in \mathbb{N} C_i \\ u_{ij}^t, x_{ik}^t \in \{0, 1\} \end{bmatrix}$

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#### MODELING OF COMBINED – CYCLE PLANTS

- > Application of a hybrid component/mode model
- Constraints can be individually enforced for the thermal units
- transition requirements between configurations can be included
- Linking constraint between units
  status and configuration modes

$$\begin{cases} \sum_{j \in NU_i} P_j u_{ij}^t = \sum_{k \in NC_i} N_k x_{ik}^t \\ \sum_{k \in NC_i} x_{ik}^t = 1 \\ u_{ii}^t, x_{ik}^t \in \{0, 1\} \end{cases}$$

 $u_{ii}^t$ 





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 $x_{ik}^t$ 

### **DC MODEL OF THE ELECTRICAL NETWORK**



#### **Line Flow limit constraints**



> phase angles are a function of power injections / loads





NE

ŚΕ

IV

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IT

#### **Ramp constraint on line flows**

$$\left|f_{km}^{t} - f_{km}^{t-1}\right| \leq \overline{\Delta f_{km}}$$

#### **Power transmission losses**

> dynamic piecewise linear approximations

$$l_i \cong g_i \Delta \theta_i^{(k)^2}$$

Line flow limits and approximations for losses are iteratively included

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[Santos,

Diniz,11]

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### ADDITIONAL SECURITY CONSTRAINTS



constraints on the relation of flows in given lines of the system for security purposes



#### PIECEWISE LINEAR CONSTRAINTS



some constraints are given by tables



UMITES DE RNE (MW)									
	Carga NE	< 10.500	10.500 ≤ Carga NE < 12.000		Carga NE ≥ 12.000				
Faixa de Recebimento / Exportação Norte	(F) = Somatório do fluxo na transformação 500/230 kV de Igaporã III, no sentido de 230 kV para o 500 kV e do fluxo na LT 230 kV Igaporã II / Bom Jesus da Lapa II, no sentido de Igaporã II para Bom Jesus da Lapa II.								
(RN / <u>Exp_N</u> )	0 < F ≤ 600	600 < F ≤ 1.050	0 < F ≤ 600	600 < F ≤ 1.050	0 < F ≤ 600	600 < F ≤ 1.050			
Exp_N ≥ 5.000	Limite = 40% da carga NE	Limite =	4.400 (1)	4.300 (1)	4.400	4.300			
4.000 ≤Exp_N< 5.000		carga NE	4.300 (1)	4.300 (1)	4.300	4.300			
3.000 ≤Exp_N< 4.000		4.200 (1)	4.200 (1)	4.200 (1)	4.200	4.200			
2.000 ≤Exp_N< 3.000		4.100 (1)	4.100	4.100	4.100	4.100			
1.000 ≤Exp_N< 2.000		3.900 (1)	4.000	3.900	4.000	3.900			
0 ≤ <u>Exp_N</u> < 1.000	4.100 (1)	3.600 (1)	4.000	3.700	4.000	3.500			
0 < RN ≤ 500	3.900 (1)	3.300 (1)	4.000	3.500	4.000	3.500			
500 < RN ≤ 1.000	3.600 (1)	3.000 (1)	3.800	3.200	4.000	3.300			
1.000 < RN ≤ 1.500	3.200 (1)	2.700 (1)	3.400	2.900	3.600	2.900			

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### OVERALL PROBLEM FORMULATION

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#### MIXED INTEGER (PIECEWISE) LINEAR PROGRAMMING $\sum \sum c_i(gt_i^t) + S_i^t + \alpha^T (V^T)$ TRANSMISSION min s.a. LOAD $\sum_{j \in \Phi} gt_j^t + \sum_{i \in \Psi} gh_j^t + \sum_{i \in Q} \left( Int_{j \to i}^t - Int_{i \to j}^t \right) = D_i^t$ E Demand i = 1, ..., NS, t = 1, ..., T,**Electrical** $\sum_{i=1}^{NB} \kappa_{i,i} (g_i - d_i) \le \overline{f_i} ; p_i - \sum_{i=1}^{NB} \kappa_{i,i} (g_i - d_i) \le rhs \qquad i, j = 1, \dots, NL, t = 1, \dots, T$ network Water $V_i^t = V_i^{t-1} + I_i^t - (Q_i^t + S_i^t) + \sum (Q_j^t + S_j^t)$ H balance $gh_i^t = FPH(V_i^t, Q_i^t, S_i^t)$ AHPF i = 1, ..., NH, t = 1, ..., T,**Operative** $V_i^t \leq V_i^t \leq \overline{V_i^t}, \ Q_i^t \leq Q_i^t \leq \overline{Q_i^t}, \ \underline{gh_i^t} \leq gh_i^t \leq \overline{gh_i^t},$ constraints **Termal** $gt_i \cdot u_i^t \leq gt_i^t \leq \overline{gt_i} \cdot u_i^t$ $Ce_i^{\tau} \left( u_i^t - \sum_{k-\tau-\tau}^t u_i^k \right) \le S_i^t \qquad Cs_i \left( u_i^{t-1} - u_i^t \right) \le S_i^t$ constraints $\sum_{k=t}^{t+Ton_i-1} u_i^k \ge Ton_i \cdot (u_i^t - u_i^{t-1})$ $\underline{GT}_{i}\left(u_{i}^{t}-\sum_{k=1}^{NU_{i}}\hat{y}_{i}^{t-k+1}-\sum_{k=1}^{ND_{i}}\tilde{y}_{i}^{t+k-1}\right) \leq GT_{i}^{t} \leq \overline{GT}_{i}\left(u_{i}^{t}-\sum_{k=1}^{NU_{i}}\hat{y}_{i}^{t-k+1}-\sum_{k=1}^{ND_{i}}\tilde{y}_{i}^{t+k-1}\right) + CT_{i}^{t}$ Unit Commitment $\sum_{k=t}^{t+Toff_{i}-1} (1-u_{i}^{k}) \ge Toff_{i} \cdot (u_{i}^{t-1}-u_{i}^{t})$ $+\sum_{i=1}^{NU_i} TrUp_i(k) \cdot \hat{y}_i^{t-k+1}$ $\sum_{i=1}^{NU_i} TrUp_i(k) \cdot \hat{y}_i^{t-k+1} +$ $u_i^t \in \{0,1\} \quad \widetilde{y}_i^t = \widetilde{w}_i^t + \left(u_i^{t-1} - u_i^t\right)$ $+\sum_{i=1}^{ND_i} TrDn_i(ND_i-k+1)\cdot \widetilde{y}_i^{t+k-1}$ $\sum_{i=1}^{ND_i} TrDn_i (ND_i - k + 1) \cdot \widetilde{y}_i^{t+k-1}$ + MANY more $\widetilde{v}_{i}^{t} + \widetilde{w}_{i}^{t} \leq 1$ i = 1, ..., NUT, t = 1, ..., T.constraints...

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Solving Strategy: MILP (1/3)

#### **ITERATIVE LP APPROACH TO FIND MAJOR / POTENTIAL BINDING CONSTRAINTS IN THE ELECTRICAL NETWORK**

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#### Solving Strategy: MILP (2/3)

# ITERATIVE LP WITH FIXED UC TO OBTAIN A GOOD (?) FEASIBLE SOLUTION

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Solving Strategy: MILP (3/3)



#### FINDING AN OPTIMAL SOLUTION WITH THE DESIRED ACCURACY



### **RECENT DEVELOPMENTS: REDUCTION OF CPU TIMES**



Use of tighter/more compact unit commitment formulations [Ostrowsku, Ra Anjos,Vanneli, 13] [M

[Dam, Kucuk, Rajan, Atam, 13]

[Morales-Espana, Latorre, Ramos, 13]

- Taking into account optimal basis informationwhile adding new constraints to the problem in a MILP setting
- Alternative (better) interaction between MILP and LP solving procedures
  - ✓ Application of local branching

#### **Hamming Metric**

$$\Delta(u,\overline{u}) = \sum_{\{v: (\overline{u})^{v} = 1\}} [1 - (u)^{v}] + \sum_{\{v: (\overline{u})^{v} = 0\}} (u)^{v}$$

[Fischetti, Lodi,03] [Saboia, Diniz,16]



### DETERMINATION OF MARKET PRICES



#### **Obtain nodal prices for all buses of the system**



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#### **PERFORMANCE RESULTS** "shadow" operation – ONS



Presentation

#### 154 REAL CASES FROM Jan 1st to Jun 13th



#### Average CPU time: 18.2min < 1 hour: ~ 96%

#Hydro Plants:158#Thermal Plants:109#Network Buses:6,800

**#Transmission Lines: 9,800** 

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