PROJECT 8 – NUMERICAL SIMULATION AND MODELLING

Prof. Dr. Bruno Souza Carmo, Prof. Dr. Julio Meneghini, Prof. Dr. Ernani Volpe, Dr. Ivan Korkischko
Department of Mechanical Engineering
Prof. Dr. Rafael dos Santos Gioria
Department of Mining and Petroleum Engineering
Prof. Dr. Celma Ribeiro
Department of Industrial Engineering
POLI – University of São Paulo, Brazil

Research Centre for Gas Innovation

cleaner energy for a sustainable future

3rd RCGI Workshop
University of São Paulo, Brazil
21 – 22 August 2018

OPTIMIZATION AND STATISTICS IN ENERGY ECONOMICS

Prof. Dr. Celma de O. Ribeiro,
Department of Industrial Engineering - POLI – University of São Paulo, Brazil
Prof. Dr. Oswaldo L. V. Costa,
Department of Telecommunications and Control Engineering- POLI – University of São Paulo, Brazil
Prof. Dr. Erik E. Rego
Department of Industrial Engineering - POLI – University of São Paulo, Brazil
Prof. Dr. Julio M. Stern
Institute of Mathematics and Statistics- IME-University of São Paulo, Brazil

Research Centre
for Gas Innovation
cleaner energy for a sustainable future

3rd RCGI Workshop
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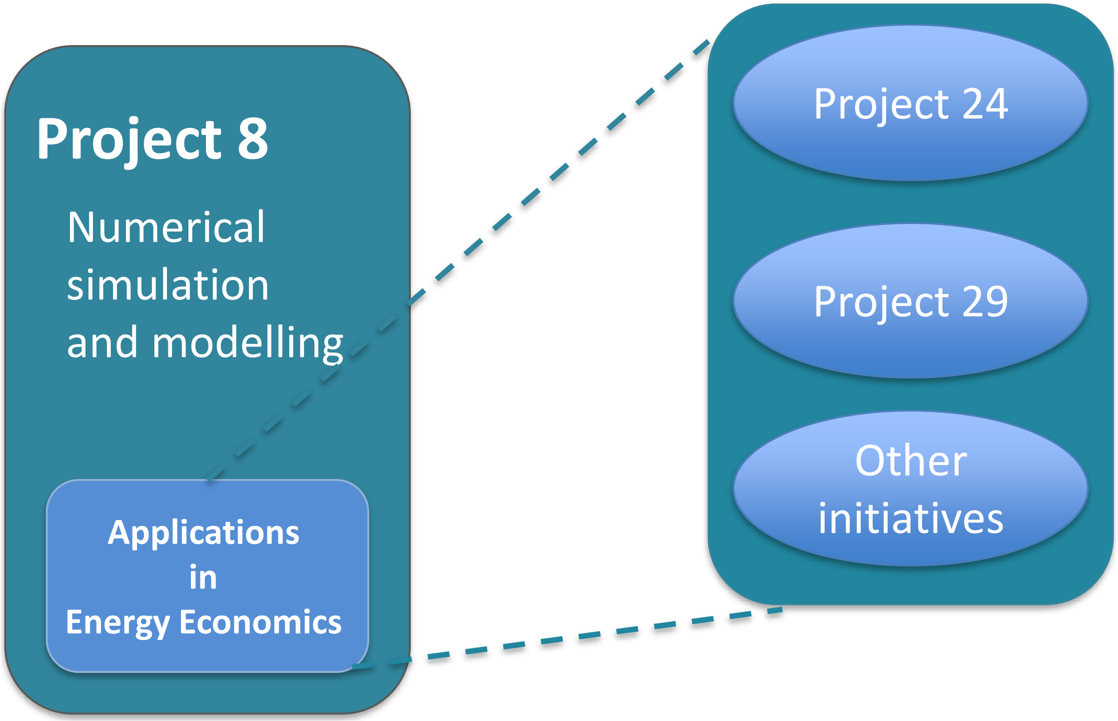
Collaboration with other projects



Main purpose

- Development and applications of mathematical tools from optimization and statistics.

Portfolio Models

RESOURCES

RISK

ASSETS

Forecasting Models

FUTURE →

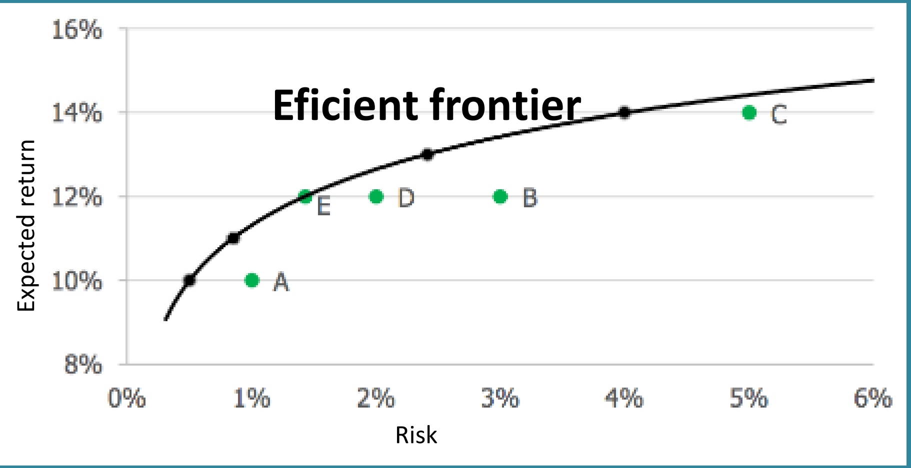
← PAST

Portfolio models

RESOURCES

RISK

ASSETS



Portfolio Theory

Consolidated approach in finance theory

Consider trade-off risk/return

Portfolios on the efficient frontier are Pareto optimal

The investor chooses a portfolio according to her/his risk aversion

The investor problem is a constrained optimization problem

Important application: Electricity Planning


Technologies

Oil

Wind

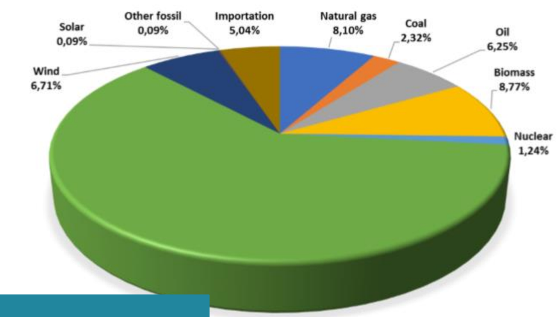
Coal

nuclear plants

Biomass

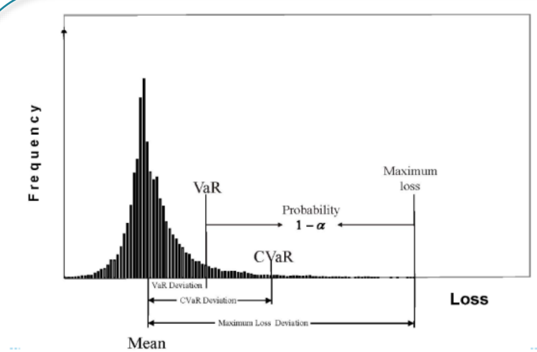
Natural Gas

hydropower plants



Solutions

Aneel, 2017



Risk: uncertainty in costs

- Traditional approach:

Covariance matrix

Portfolio mix

$$\min_{\omega} \ \omega' \Psi \omega$$

$$\text{subject to } \omega' r = \tau, \quad \omega \in \Gamma.$$

Constraints

Expected Costs

Important application: Electricity Planning

Challenge:

The consideration of the uncertainties associated with the future costs of technologies is crucial for planning purposes.

Alternative approaches

Robust optimization

Parameters inside an uncertainty set

$$\min_{\omega \in \Gamma} \max_{(r,\Psi) \in \mathcal{U}} \left(\omega' r + \lambda \omega' \Psi \omega \right).$$

Bayesian optimization

Parameters are random variables with known probability distribution

$$\min_{\omega \in \Omega} \omega' \tilde{\mu} + \lambda \omega' \tilde{\Sigma} \omega.$$

$$C | \tilde{\mu}, \tilde{\Sigma} \sim t_{T-2N} (\tilde{\mu}, \tilde{\Sigma}), T - 2N \geq 2 \qquad \tilde{\mu} = \hat{\mu} \text{ and } \tilde{\Sigma} = \frac{(1 + T^{-1})(T-1)}{T - 2N - 2} \hat{\Sigma}.$$

Results: Robust Portfolio (Electricity)

Energy Economics 64 (2017) 158–169

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

ELSEVIER

Robust portfolio optimization for electricity planning: An application based on the Brazilian electricity mix

Oswaldo L.V. Costa[a,*], Celma de Oliveira Ribeiro[b], Erik Eduardo Rego[b], Julio Michael Stern[c], Virginia Parente[d], Solange Kileber[d]

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[b] Department of Production Engineering, EPUSP, São Paulo 05508-070, SP, Brazil
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Collaboration with Project 24

Results: Robust Portfolio (Electricity)

Table 6
Weights, exp. costs (cents USD/KWh), STD, CO_2 emission (TM/KWh) for Ref. 2024, optimal and robust mixes.

Fuel	Ref. 2024	Optimal	Poly. (Eq. (14))	Poly. (Eq. (16))	Box Eq. (27))	Ellip. Eq. (13))
Gas	10.96%	11.69%	12.25%	12.15%	5.87%	11.94%
Coal	1.7%	2.88%	1.54%	1.82%	1.53%	3.13%
Nuclear	1.7%	2.00%	2.00%	2.00%	2.00%	2.00%
Fuel oil	2.16%	2.42%	2.41%	2.41%	2.42%	2.41%
Biomass	9%	5.56%	5.57%	5.59%	5.56%	5.57%
Hydro	58.56%	55.72%	56.51%	56.78%	63.21%	60.17%
Wind	12%	14.00%	14.00%	13.53%	13.68%	9.05%
Small hydro	3.92%	5.73%	5.72%	5.72%	5.73%	5.73%
Exp. cost	7.155	7.155	7.155	7.153	7.155	7.155
Stand. dev	0.0420	0.0393	0.0451	0.0456	0.0495	0.0455
CO_2 emis.	0.0728	0.0879	0.0780	0.0802	0.0518	0.0912

2024 Decennial Plan for Energy Expansion

Alternative uncertainty sets

Results: Robust Portfolio (Electricity)

Nominal data

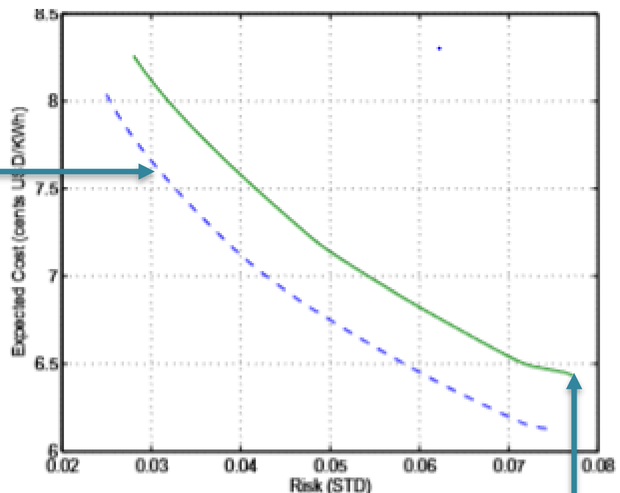

Fig. 2. Efficient frontier for the nominal data (dashed line) and the high CO_2 emission cost data (solid line).

Considering CO2 costs
Box uncertainty

Nominal data

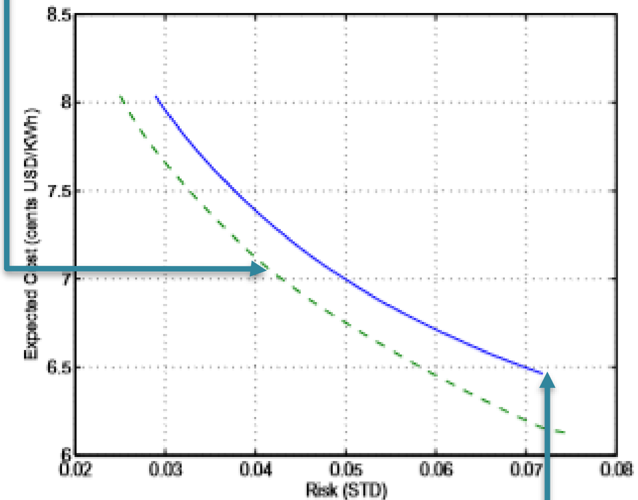

Fig. 3. Efficient frontier for the nominal data (dashed line) and the robust problem (13) with ellipsoidal uncertainty set for *r* (solid line).

Robust model
Ellipsoidal uncertainty

Results: Robust Portfolio (Biogas and bioelectricity)

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The insertion of biogas in the sugarcane mill product portfolio: A study using the robust optimization approach

Raphael de Moraes Dutenkefer*, Celma de Oliveira Ribeiro, Victoria Morgado Mutran, Erik Eduardo Rego

Escola Politécnica da Universidade de São Paulo, São Paulo, Brazil

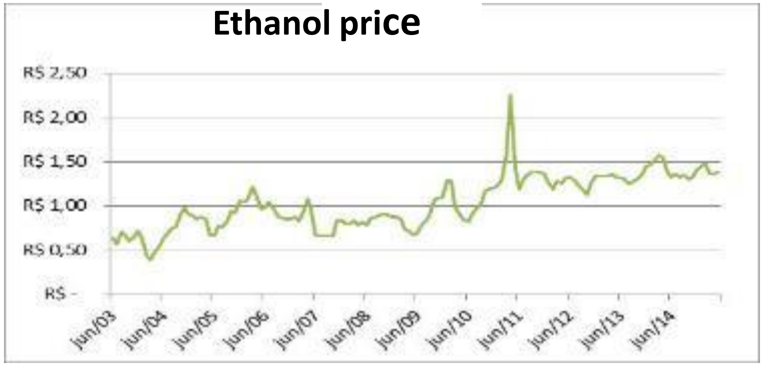
Results: Robust Portfolio (Biogas and bioelectricity)

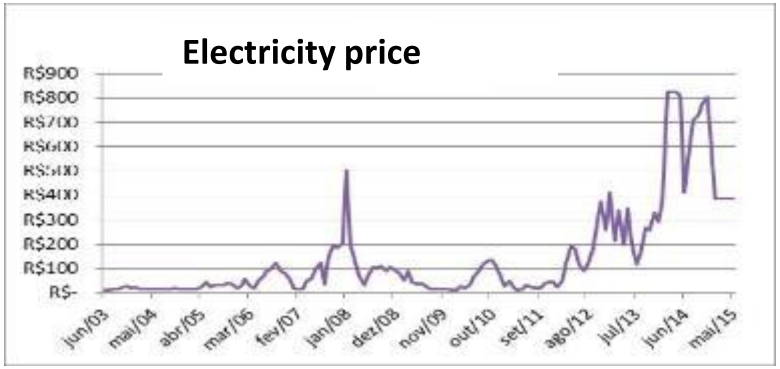
Product portfolio- sugarcane industry

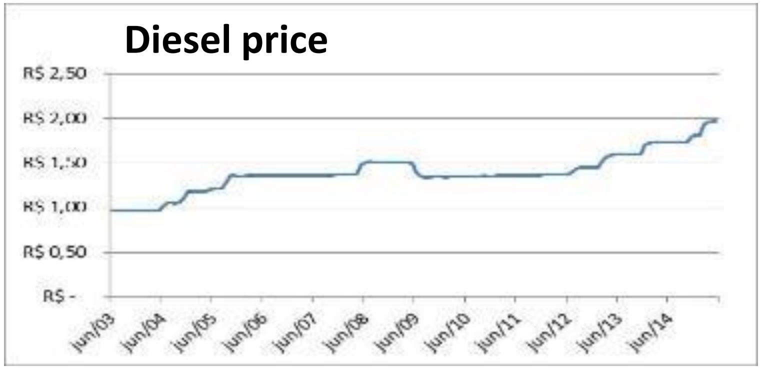
- Analysis of the economic impacts of biogas insertion in the **product mix** of sugarcane mills (ethanol, sugar, and electricity).
- A portfolio model was developed respecting all operational constraints (CVaR is the risk measure).
- Uncertainties in the market prices
- Use of robust optimization techniques to mitigate the consequences of such price variations.

Results: Robust Portfolio (Biogas and bioelectricity)

Sugarcane industry: uncertainty on prices

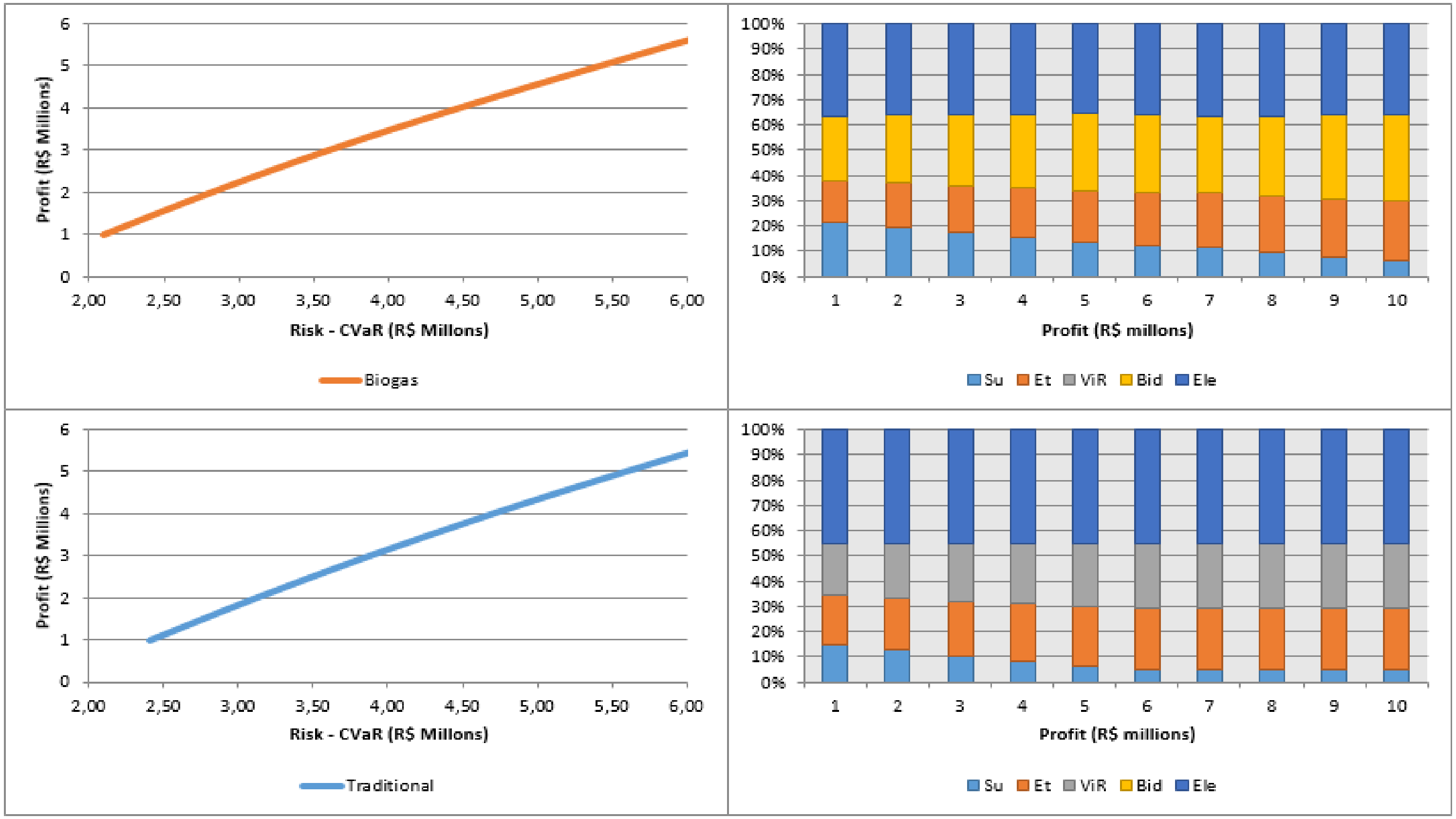






Results: Robust Portfolio (Biogas and bioelectricity)

Efficient Frontiers and Portfolios



Results: Bayesian Portfolio (Electricity)

entropy

MDPI

Article

Classical-Equivalent Bayesian Portfolio Optimization for Electricity Generation Planning †

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† This paper is an extended version of our paper published in 37th International Workshop on Bayesian Inference and Maximum Entropy Methods in Science and Engineering, Jarinu, Brazil, 9–14 July 2017.

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Results: Bayesian Portfolio (Electricity)

- The application of the approach was analyzed using improper and proper priors

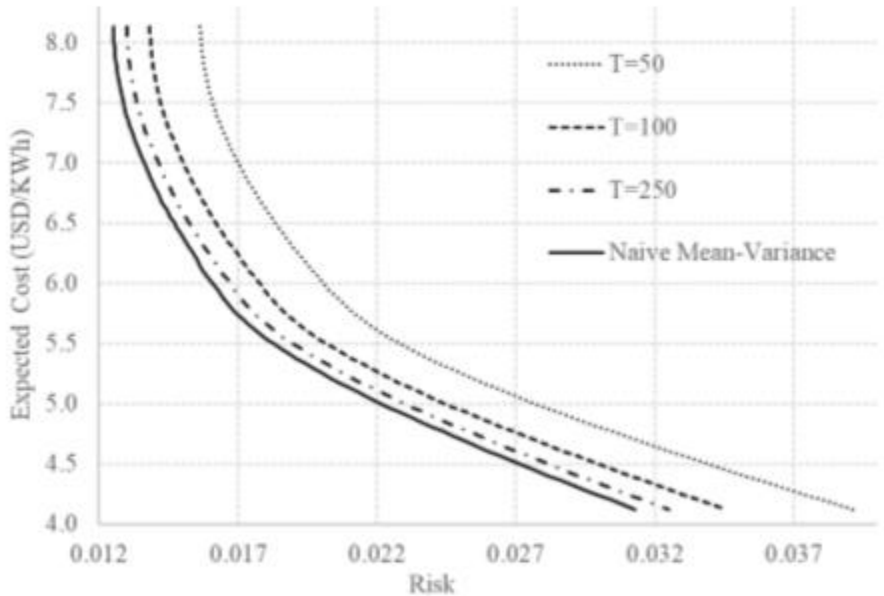


Figure 1. Efficient frontiers using naive and classical-equivalent Bayesian approaches for the improper prior case for some values of T.

Improper priors

The investor has no information about the distribution of parameters

T is the number of historical observations

Results: Bayesian Portfolio (Electricity)

- The application of the approach was analyzed using improper and proper priors

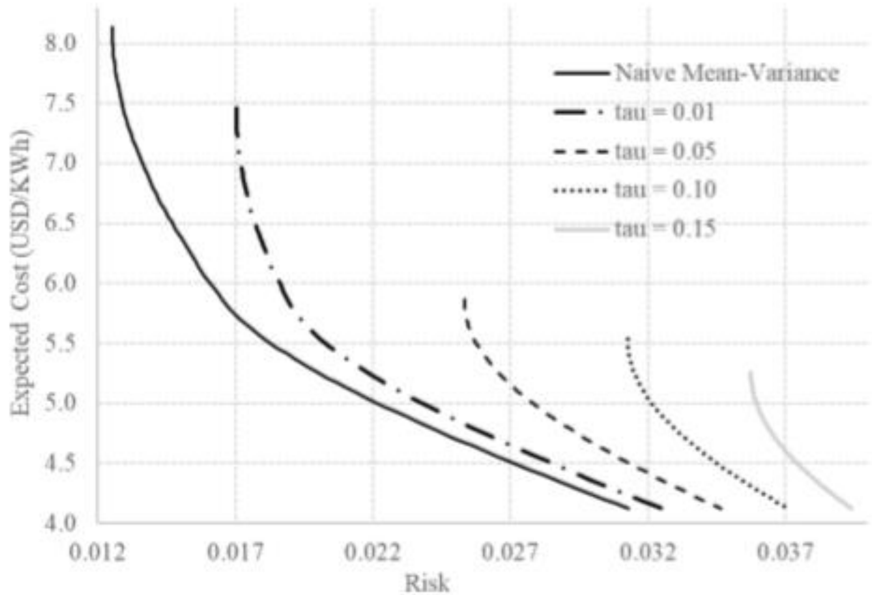


Figure 2. Efficient frontiers using naive and classical-equivalent Bayesian approaches for the proper prior case for some values of τ.

Proper priors

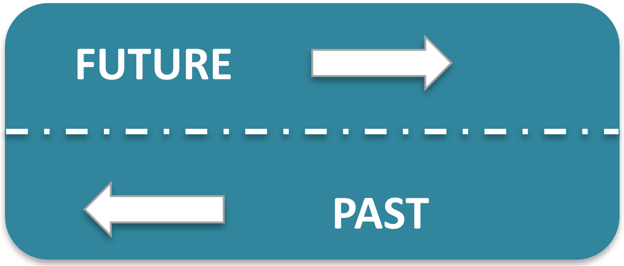
Specialists have informative beliefs about the mean and covariance of technology costs.

Tau represents the confidence strength the specialist places on the value of expected costs

$$\mu|\Sigma \sim N\left(\eta, \frac{1}{\tau}\Sigma\right), \Sigma \sim W^{-1}(\Psi, \nu),$$

expected costs based on the specialist experience

Forecasting models



Challenge:

The analysis of energy demand through statistical models

Alternative approaches

- **Use and analysis of econometric models**
  - Electricity Crisis
  - Price Elasticity
- **Improvement of econometric models**
  - Short time series
- **Use of hybrid models**
  - Gas for light vehicles

Results: Analysis of Brazilian Electricity Crisis

Energy Policy 106 (2017) 266–277

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ENERGY POLICY

Thermoelectric dispatch: From utopian planning to reality

CrossMark

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Results: Analysis of Brazilian Electricity Crisis

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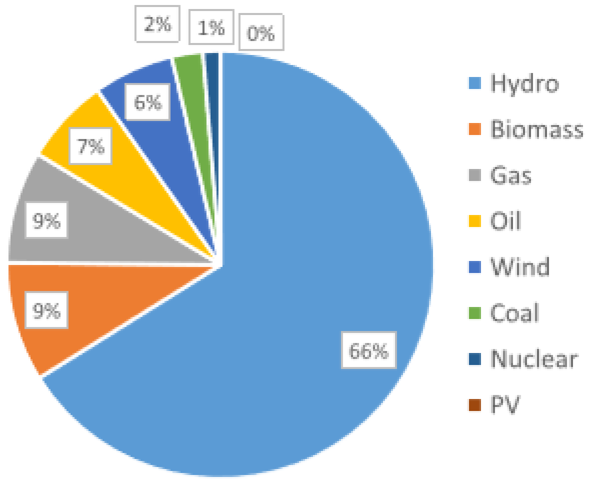

Fig. 1. Brazilian electricity matrix.
Source: ANEEL (2016).

Historically hydropower accounts for more than 80% of power generation in Brazil

The lack of water in the reservoirs leads to serious crisis (e.g 2013-2015)

Why???

Results: Analysis of Brazilian Electricity Crisis

- Thermoelectric dispatch

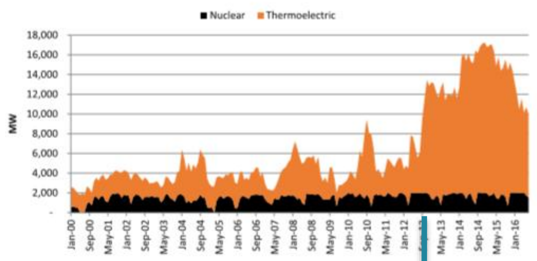

Fig. 4. Brazilian thermoelectric power generation. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)
Source: ONS, 2016.

2013

Hypothesis regarding the causes

- divergence between the planning and execution of the expansion of power generation and transmission,
- the weakness of the NEWAVE dispatch software used by the government
- the below-average hydrology in 2014 and 2015.

Linear regression models were developed to forecast the electricity demand.

Specialists forecast of the hydroelectricity supply

Results: Analysis of Brazilian Electricity Crisis

Demand forecast through linear models

(including seasonality, trend and dummies to represente the effect of crisis)

Table 1
Estimates of the coefficients (s.e. and p-values) of the regression model for the electricity demand of the industrial sector (Coefficient of determination R^2=0.94).

Relevant Covariates for Y_{1t}= the electricity demand of the industrial sector	Estimated coefficients	s.e.	*p*-Value
constant	−46650	10349	0.000
X_1= the electricity fare of the industrial sector	20.08	1.99	0.000
X_3= the electricity fare of the commercial sector	−16.31	2.09	0.000
X_5= the population	374.2	66.0	0.000
X_6= the per capita gross domestic product	−9.022	0.567	0.000
X_8= the gross industrial product	0.152	0.013	0.000
X_{11}= trend	−404.0	128.0	0.002
X_{12}= effect of the Brazilian energy crisis	−565.0	210.0	0.008

Table 2
Estimates of the coefficients (s.e. and p-values) of the regression model for the electricity demand of the residential sector (Coefficient of determination R^2=0.98).

Relevant Covariates for Y_{2t}= the electricity demand of the residential sector	Coefficients	s.e.	*p*-Value
Constant	27,181	4050	0.000
X_2= the electricity fare of the residential sector	−1.049	0.335	0.000
X_5= the population	−137.5	25.8	0.000
X_6= the per capita gross domestic product	1.43	0.19	0.000
X_9 = seasonality (cos)	232.2	24.0	0.000
X_{11}= trend	533.2	52.2	0.000
X_{12}= effect of the Brazilian energy crisis	−1656.5	84.5	0.000

Results: Analysis of Brazilian Electricity Crisis

Table 3
Estimates of the coefficients (s.e. and p-values) of the regression model for the electricity demand of the commercial sector (Coefficient of determination R^2=0.98).

Relevant Covariates for Y_{3t}= the electricity demand of the commercial sector	Coefficients	s.e.	*p*-Value
Constant	3491	135	0.000
X_3= the electricity fare of the commercial sector	−2.554	0.356	0.000
X_9 = seasonality (cos)	228.9	19.4	0.000
X_{11}= trend	283.60	4.44	0.000
X_{12}= effect of the Brazilian energy crisis	−737.1	72.6	0.000

Table 4
Estimates of the coefficients (s.e. and p-values) of the regression model for the electricity demand of the other sectors (Coefficient of determination R^2=0.98).

Relevant Covariates for Y_{4t}= the electricity demand of other sectors	Coefficients	s.e.	*p*-Value
Constant	−17,800	1944	0.000
X_5= the population	75.30	6.20	0.000
X_6= the per capita gross domestic product	0.705	0.086	0.000
X_7= the GINI index	14,148.0	1915.0	0.000
X_9 = seasonality (cos)	59.4	11.9	0.000
X_{12}= effect of the Brazilian energy crisis	−471.7	42.2	0.000

Demand forecast
Linear models

Supply scenarios
(specialists)

Newave model

NG demand for thermoelectricity

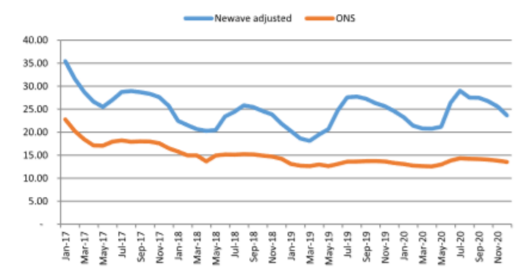

Fig. 22. Projected natural gas consumption for thermal dispatch (million m3/day): ONS scenario versus sensitive analysis.
Source: authors

Next steps  (papers submitted)

Improvement of econometric models

Use of robust optimization in parameter estimation for linear models

Use of hybrid models

Use of hybrid models (econometric + Neural Networks) to GNV forecasting

Next steps  (being studied)

Intentional sampling techniques

Apply Haphazard Intentional Sampling techniques to rationally re-engineer networks of measurement stations for atmospheric pollution and/or gas emissions

Hybrid and conventional vehicles for distribution in urban centers

With Project 29

Pre-salt Natural Gas for electricity generation

evaluate economic aspects of the generation of electricity from the natural gas from the Pre-salt,
gas to wires versus Floating Liquefied Natural Gas (FLNG) technology for onshore generation

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