Modelos Matemáticos de Otimização Sob Incertezas

Project OTIM-PBR: A Stochastic Programming Approach to Brazilian Oil Supply Chain Planning



Agenda

- 1. Project Team
- 2. Brazilian Oil Supply Chain
- 3. Current Approach
- 4. Uncertain Sources
- 5. Proposed Approach
 - a. Statistical Model
 - b. Optimization Model
- 6. Conclusions

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OTM-PBR: Academic Team



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The setting





Brazil's supply chain



Brazil's supply chain



Curde Oil:

- Imports (1)
- Exports (3)
- Production (5)
- Oil Products:
 - Imports (2)
 - Exports (4)
 - Market Selling (6)
- ~ 200 different crude oils
 - ~ 50 different oil products

10 basins of oil production
23000 km pipelines
>100 platforms
> 40 terminals in Brazil
>200 terminals abroad
13 refineries

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Supply chain planning tool Computational model

PlanAb

Computational model for Petrobras supply chain
Tool to determine the optimal planning for the whole supply chain of the company for the next month.

 Currently PlanAb is a deterministic model that solves a large scale linear programming problem

$$\begin{cases} \min_{x,y} c^{\top}x + q^{\top}y \\ \text{s.t} & Ax & = b \\ & Tx + Wy = h \\ & \underline{x} \leq x \leq \overline{x} \\ & \underline{y} \leq y \leq \overline{y} \\ & y_i & = \overline{y}_i & i \in I_V \end{cases}$$

Supply chain planning tool Computational model

PlanAb

$$\begin{array}{rcl}
\min_{x,y} & c^{\mathsf{T}}x &+ q^{\mathsf{T}}y \\
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& y_i &= \overline{y}_i & i \in I_V
\end{array}$$

Availability of oil volume from the plataforms

Variable x represents commercial transactions such as imports along the planning horizon (four months)
Variable y represents exports and logistic operations such transportation and refinery oil/derivative production





Objective function PlanAb model

Current model:

$$\min_{x,y} c^{\top}x + q^{\top}y$$

Model (objective function)

Costs

- •Oil imports
- •Derivative imports
- •Derivative storage
- •Refining unit operations
- •Transportation

Revenues

Oil exportsDerivative exportsDerivative national sales



Variables and constraints PlanAb model

1.Oil and derivatives balance

Includes all constraints involving the system balance of oil/derivatives and how they flow in the network
Balancing the derivatives in each terminal and refinery

$$Ax = b$$

$$Tx + Wy = h$$

$$\underline{y} \leq y \leq \overline{y}$$

$$\underline{y}_{i} = \overline{y}_{i} \quad i \in I_{V}$$

PlanAb

Deterministic

$$\min_{x,y} c^{\top}x + q^{\top}y$$
s.t
$$Ax = b$$

$$Tx + Wy = h$$

$$\underline{x} \leq x \leq \overline{x}$$

$$\underline{y} \leq y \leq \overline{y}$$

$$y_i = \overline{y}_i \quad i \in I_V$$

2

How large are these models?

Deterministic PlanAb

Implemented in AIMMS

LP's dimension:
2.3 million of variables
1.7 million of constraints

Constraints' matrix:
 Sparse (0,0002% non-zero elements; approximately 7.3 million of elements)
 Block-diagonal structure

ſ	$\min_{x,y}$	$c^{\top}x$	+	$q^{\top}y$	
	s.t	Ax			= b
		Tx	+	Wy	= h
		$\underline{x} \leq$	x	$\leq \overline{x}$	
		$\underline{y} \leq$	y	$\leq \overline{y}$	
		y_i	=	$ar{y}_i$	$i \in I$



Deterministic PlanAb

PlanAb LP:

2.3 million of variables, 1.7 million of constraints
7.3 million of non-zero elements (0.0002% - sparse matrix)
After presolve, problem size reduced approximately by 80%

Model	Variables	Constraints	Non-zero elements	Presolve time (sec)		
Original	2.3 million	1.7 million	7.3 million	0		
Conservative presolve	644,000	307,000	2.88 million	2.7		
Automatic presolve	385,000	94,000	2.19 million	11.1		
Aggressive presolve	385,000	92,000	2.14 million	13.2		

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Production flow PlanAb

Simplified Network





Oil Production



- Naturally oil fields have a production curve along the time.
 - Some technics are applied to smoothing the curve, the result of this technics are not deterministic
- Maintenances whose duration is subject to uncertainties



Oil Production Log-logistic Distribution







• Volatility is a natural attribute of the historical curve of oil and derivatives prices, with high uncertainty.





2





Uncertainly - Impact

	Atmospheric Distillation 1					Atmospheric Distillation 2						
	QAV		Naphtha		Diesel		QAV		Naphtha		Diesel	
	% Vol	% S	% Vol	% S	% Vol	% S	% Vol	% S	% Vol	% S	% Vol	% S
Oil 1	9,6	0,178	16,4	0,028	28,0	1,516	13,3	0,145	5,0	0,020	30,0	1,071
Oil 2	6,2	0,203	3,6	0,015	26,9	0,586	7,6	0,179	1,1	0,003	29,0	0,499
Oil 3	3,2	0,228	2,3	0,035	22,8	0,514	4,2	0,207	0,2	0,011	24,8	0,452
Oil 4	5,4	0,199	5,7	0,011	25,9	0,591	7,0	0,174	1,4	0,000	27,9	0,504
Oil 5	5,7	0,259	5,4	0,014	27,7	0,596	7,2	0,224	1,5	0,003	29,7	0,517
Oil 6	11,2	0,015	26,2	0,009	24,0	0,050	15,6	0,016	9,0	0,006	25,4	0,037



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Stochastic Optimization

Two- Stage Stochastic Linear Program with Recourse

- Divides the decision variables in two stages.
- First stage variables must be decided prior to uncertainties.
- Second stage variables correct the solution after the completion of uncertainties.

$$\operatorname{Min}_{x\in X}\left\{z\left(x\right)=c^{T}x+\sum_{s=1}^{S}p_{s}Q_{s}\left(x,\xi_{s}\right)\right\}$$

- In the first stage, the decision is *here and now*, prior to the uncertainties.
- The decision taken at the second stage problem reflects the optimal behavior at the time uncertainty is disclosed

Stochastic Optimization Measuring an optimization under uncertainties

- Expected (or mean) value problem: $EV = \min_{x} z(x, \overline{\xi}), \overline{\xi} = \mathbb{E}[\xi]$
- The expected result of using the EV solution measures the performance of $\overline{x}(\overline{\xi})$ (optimal second-stage reactions given $\overline{x}(\overline{\xi})$):

$$EEV = \mathbb{E}_{\xi}[z(\bar{x}(\bar{\xi}),\xi)]$$

Value of the Stochastic Solution - VSS
 - VSS = EEV - RP



Computational model

• Block 1: Statistical

- Tool generating scenarios for:
- International prices (oil and derivatives, correlated)
- Oil volume arriving from the platforms each month.
- Technique: multivariate model + Kalman filter + SDP NLP solver, assessed by backtesting .
- Block 2: Optimization
 - Tool to determine the optimal policy for the whole supply chain of the company for the next month. It includes:
 - To which extent the company network (of production, transportation, commercialization) can be simplified?
 - How to handle uncertainty in the optimization problem (in the cost and in the right hand side Problem solution via decomposition method huge scale problem)

Some comments

- Uncertainty increases the (already huge) size of the linear program (LP).
- Mounting the data for the deterministic model takes longer than solving the LP.
- Solving an aggregate model is not an option: keeping the level of detail of the deterministic model is important for the company.
- BUT
 - Changing CPLEX stopping tolerance from default 10⁻⁸ to 10⁻⁴ provides a good trade-off between accuracy and solving time:
 - mean relative error on variables 0,007%
 - solving times reduced in 18,56%



Statistical Block

2

Sources of uncertainty Calibration of price models

- 1. Oil, gasoline and diesel international prices
 - The model is a process defined by stochastic differential equations.
 - To determine the parameters defining the model (mean, trend, volatility, correlations) we maximize the proximity to historical data (likelihood) using a Kalman filter.
 - Small scale non-convex optimization problem, solved by a nonlinear programming method of interior feasible directions.

Sources of uncertainty Calibration of price models

- They should include important oil price features such as picks, seasonality, mean reversion, etc.
- There are several stochastic processes for modelling commodity prices.
- The models are completely described by certain parameters that can be time dependent (mean, trend, volatility, correlations) and whose values need to be estimated (calibration).



Optimization Block

2
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Objective function PlanAb model

Current model:

$$\min_{x,y} c^\top x + q^\top y$$

Model (objective function)

 $x, y(\boldsymbol{\xi})$

Co	sts

Revenues

•Oil imports

- •Derivative imports
- •Derivative storage
- •Refining unit operations
- •Transportation

•Oil exports

•Derivative exports

•Derivative national sales



min $c^{\top}x + \mathbb{E}[q(\xi)^{\top}y(\xi)]$

Proposed model:

Variables and constraints PlanAb model

1.Oil and derivatives balance

Includes all constraints involving the system balance of oil/derivatives and how they flow in the network
Balancing the derivatives in each terminal and refinery

$$\begin{array}{ll} Ax & = b \\ Tx & + Wy & = h \end{array}$$

Considering adjustments on the available oil for:
Processing in the refineries
Exportation, when the volume of oil arriving from the platforms is larger than foreseen

$$egin{array}{ccc} \underline{y} &\leq \overline{y} \ \overline{y}_i &= egin{array}{ccc} \overline{y}_i &i \in I_V \end{array} \end{array}$$

Sources of uncertainty

1.Oil, gasoline and diesel international prices 2.Stochastic process: multivariate Schwartz-Smith

This uncertainty is represented by

1.Availability of national oil2.The ratio between the foreseen and observed volumes follows a log-logistic probability distribution

This uncertainty is represented by ω

WO different sources of uncertainty!



Deterministic PlanAb

PlanAb LP:

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Stochastic PlanAb

$\min_{x,y}$	$c^{\intercal}x$	+	$\mathbb{E}[q(\pmb{\xi})^{\top}y(\pmb{\xi},\omega)]$	
s.t	Ax			= b
	Tx	+	$Wy(\boldsymbol{\xi}, \boldsymbol{\omega})$	= h
	$\underline{x} \leq$	x	$\leq \overline{x}$	
	$\underline{y} \leq$	$y(oldsymbol{\xi},oldsymbol{\omega})$	$\leq \overline{y}$	
	$y_i(oldsymbol{\xi},oldsymbol{\omega})$	=	$ar{y}_i(\omega)$	$i \in I_V$
	$\forall \xi \in \Xi$		$\omega \in \Omega$	

 Problem's size depends on the number of scenarios of price and oil volume

Number of variables is N times 2.3 million
Number of constraints is N times 1.7 million

•Impossible to load the problem in a (powerful) compare for N>10! (Memory issues) $N = |\Xi| * |\Omega|$

Two-stage decomposition Stochastic PlanAb

with

Consider finitely many scenarios of price and oil volume
The problem is decomposed into two decision levels



$$Q(\boldsymbol{x};\boldsymbol{\xi},\boldsymbol{\omega}) \begin{cases} \min_{y} q(\boldsymbol{\xi})^{\top} y \\ \text{s.t} \quad Wy = h - T\boldsymbol{x} \\ \underline{y} \leq y \leq \overline{y} \\ y_i = \overline{y}_i(\boldsymbol{\omega}) \quad i \in I_V \end{cases}$$

Two-stage decomposition Stochastic PlanAb

with

Consider finitely many scenarios of price and oil volume
The problem is decomposed into two decision levels

 $\begin{cases} \min_{x} c^{\top}x + \sum_{i=1}^{N} p_{i}[Q(x; \boldsymbol{\xi}_{i}, \boldsymbol{\omega}_{i})] \\ \text{s.t} \quad Ax = b \\ \underline{x} \leq x \leq \overline{x} \end{cases}$

$$Q(\boldsymbol{x};\boldsymbol{\xi},\boldsymbol{\omega}) \begin{cases} \min_{y} q(\boldsymbol{\xi})^{\top} y \\ \text{s.t} \quad Wy \quad = h - T\boldsymbol{x} \\ \underline{y} \leq \quad y \quad \leq \overline{y} \\ y_{i} \quad & = \overline{y}_{i}(\boldsymbol{\omega}) \quad i \in I_{V} \end{cases}$$

Two-stage decomposition Stochastic PlanAb















•N linear programming problems must be solved for every first-

stage decision x^k

ĺ	\min_{y}	$q(\pmb{\xi})^\top y$			
$Q(x; \boldsymbol{\xi}, \boldsymbol{\omega})$	s.t	Wy	=	h - Tx	
£(~, \$,~)		$\underline{y} \leq$	y	$\leq \overline{y}$	
	(y_i	=	$ar{y}_i(\omega)$	$i \in I_V$

This is a difficult task for large values of N

We may solve the LPs in a approximate manner (inexact cuts)
Use more efficient cutting-plane methods, such as Bundle Methods:

Convex proximal bundle methods in depth: a unified analysis for mexact oracle Math. Programming, 2014, 148, 1-2, pp 241-277 W. de Oliveira, C Sagastizábal and C. Lemaréchal.

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Conclusions

- Stochastic PlanAb
 - Price scenarios
 - Oil volume
 - can be modelled either by using scenarios or chance-constraints
 - follow independent log-logistic probability distributions
- The computational implementation of the stochastic PlanAb model, with price scenarios and chanceconstraints for oil volumes is in progress
- Challenge of modeling and computational performance
- Due to the problem of features there are enormous potential gain

Stochastic optimization models for short-term oil production



The team



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• This work is part of a larger project between Petrobras and Tecgraf (PUC-Rio)

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The OIL production process



The OIL production process



The problem

- For a system in steady-state, find the optimal values of
 - Gas-lift
 - Wellhead pressure
 - Well opening and closing (O/C)
 - that optimize the production.
- The in-house software Marlim is used to simulate the oil production for given values of the gas-lift and wellhead pressure.



Current status

- Petrobras currently uses the model **BR-SiOP** (Teixeira 2013) to solve this problem.
 - The model that computes the values of gas-lift, wellhead pressure and well O/C that optimize the production, subject to constraints on capacity of fluid treatment.
 - The output from Marlim is modeled as a piecewise linear



By using binary variables to represent the piecewise linear approximation, the resulting model is a <u>mixed linear integer optimization</u> problem which can be solved with commercial optimization software.



Shortcomings of br-siop

- While BR-SiOP has had significant impact on the oil production process, it has some drawbacks:
 - It does not consider randomness of some important parameters of the process such as the Gas-Oil Ratio (GOR) and the Water Cut (WC).
 - The use of binary variables to model the oil production curves hampers the extension to larger cases - for instance, if one wants to consider different scenarios of GOR and WC.

IMPACT OF GOR AND WC ON PRODUCTION

1200 2400 2300 1100 0 Oil production(m³/day) 000 00011 000 Oil production(m³/day) WC = 34.89 GOR = 310 - WC = 37.4 GOR = 876 GOR = 928 • WC = 40.99 0 GOR = 1004 • WC = 41.07 - WC = 41.94 GOR = 1116 GOR = 1327 -- WC = 43.84 0 - GOR = 1903 - WC = 46.54 1900 0 800-8 1800 1.0×10⁵ 1.5×10⁵ 2.0×10⁵ 5.0×10⁴ 0 5.0×10⁴ 1.0×10⁵ 1.5×10⁵ 2.0×10⁵ 0 Gas-lift(Nm³/day) Gas-lift(Nm3/day) ۶

Well K, GOR(Nm3/day) 162.94, WHP(kgf/cm2) 5.0 with different WC(%)

Well C, WC(%) 0.08, WHP(kgf/cm²) 90.0 with different GOR(Nm³/day)

A stochastic optimization model

- We propose a two-stage stochastic optimization model for the problem.
- The main idea is to provide <u>baseline values</u> of gas-lift, wellhead pressure and well O/C that protect against the variations in GOR and WC, represented by <u>scenarios</u>.
- The second stage of the problem allows for controlled deviations from the baseline values of gas-lift.

Schematic representation



Concave approximations of production function

- As the complexity of solving the oblem grows with the numbers of scenarios, we consider concerve approximations of the production curve that do not require (millions of integer variables.)
- Idea: points at non-concave regions are unlikely to be optimal.





The model

• Constraints (2nd stage):

- Oil production: $\hat{q}\left(q_{gl}^{2,n}(\omega),whp^{n},\omega\right)$
- Linking constraints: $d(\omega) = \sum_{a} q_g^n(\omega)$,

 $q_{gas-lift}(\omega) = \sum_{n \in \mathcal{N}} q_{gl}^n(\omega),$

$q_{exp}(\omega) = q_{gas-prod}(\omega) - q_{flare}(\omega) + q_{turbine}.$

- Capacity constraints on compression, flare, exportation, and water and liquid treatment.
- GOR, WC defining constraints: $q_g''(\omega) = GOR^n(\omega) \cdot q_o(\omega), \quad \forall n \in \mathcal{N}.$

 $q_w^n(\omega) = rac{WC^n(\omega)}{1 - WC^n(\omega)} \cdot q_o(\omega), \ \ orall n \in \mathcal{N}.$

 $<\Gamma \overset{\bullet}{\cdot} q_{al}^{1,n}, \ orall n \in \mathcal{N}.$

- Well opening/closing: $q_{gl,min}^n \leq q_{gl}^{2,n}(\omega) \leq t^n \cdot q_{gl,max}^n \quad \forall n \in \mathcal{N}.$

The user-defined parameter Γ controls the maximum deviation (in %) from the baseline values

Generating scenarios

- The stochastic optimization model requires scenarios of GOR and WC.
- We used past measurements to forecast future values of these parameters using <u>L1-filters</u>, and then solved the problem for sampled scenarios.
 - This procedure is called <u>Sample Average Approximation</u> (Kleywegt et al. 2002).
 - We also applied techniques from the literature to determine an appropriate number of sampled scenarios.



L1 filters: illustration



results

- We tested our model with real data of a platform with 11 wells.
- The distribution of GOR and WC was assumed to be independent across wells.
 - If correlations among wells can be reliably estimated, it is easy to generate correlated samples.
- We considered 4 values for the deviation parameter Γ (0%, 5%, 10%, 20%).
- We used 1,000 scenarios of GOR and WC.
- Code was implemented in Julia/JuMP.

Optimal solution,

		33.3%			66.6%			100%		
1	RP	VSS	(%)	RP	VSS	(%)	RP	VSS	(%)	
0.0	3121	70.2	2.25	4952	0.4	0.01	6213	11.5	0.19	
0.05	3148	65.4	2.08	4965	3.2	0.06	6232	15.5	0.25	
0.2	3193	38.4	1.20	4986	1.1	0.02	6257	5.5	0.09	
	12 	4	XO							
								-	*	
								00		

2

Compression Capacity
OPTIMAL PRODUCTION CURVES

• Production curves per scenario of GOR, WC for one of the wells



Optimal values of gas-lift for each scenario are marked with a circle.

The dashed line corresponds to the baseline solution.

The curves are plotted for the optimal value of wellhead pressure.



Comparison with the deterministic model

- We compared our model with a deterministic model that uses the average values of GOR and WC.
- The comparison is made by
 - 1. Computing the objective function value of the two-stage model at the solution given by the deterministic model, and
 - 2. Comparing it with the optimal objective value of the two-stage model.
- Some observations:
 - When the deterministic solution is feasible, the difference is small.
 - However, the deterministic solution is often <u>infeasible</u> for some scenarios due to capacity constraints- for instance, when either GOR or WC are high.
 - This suggests that the one of the benefits of the stochastic model is the adaptation of the solution to the observed scenarios of GOR and WC.



Conclusions

- We have presented a model for oil production that takes into account uncertainties in the composition of the oil such as the gas-oil ratio and water cut.
- The model produces a baseline solution as well as a solution adapted to each scenario of uncertainty that does not deviate too much from the baseline solution.
- The adaptation to scenarios ensures feasibility of the solutions.
- Future work includes, among other tasks:
 - The incorporation of uncertainty of reservoir parameters.
 - Integration with other forecast methods for GOR and WC.
 - Implementation of the strategy suggested by the model.

THANK YOU

And thanks to PETROBRAS and EMBRAPIII

