AN APPROXIMATION SCHEME FOR **Risk Averse**

STOCHASTIC EQUILIBRIUM PROBLEMS

Claudia Sagastizábal

(visiting researcher IMPA)

mailto:sagastiz@impa.br http://www.impa.br/~sagastiz

Limoges, Terry Fest, May 18th, 2015

joint work with J.P. Luna (UFRJ) and M. Solodov (IMPA)

What this talk is about?

Large-scale variational inequalities $VI(F, C) : \langle F(\bar{q}), q - \bar{q} \rangle \ge 0 \forall \text{ feasible } q = (q^0, \dots, q^N)$ $- \text{ with VI operator } F(q) = \prod_{i=0}^{N} F^i(q)$ $- \text{ with VI feasible set } C = \prod_{i=0}^{N} Q^i \bigcap \{q : MC(q) = 0\}$

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Large-scale variational inequalities
VI(F, C): ⟨F(q̄), q - q̄⟩ ≥ 0 ∀ feasible q = (q⁰,...,q^N)
- with VI operator F(q) = ∏_{i=0}^N Fⁱ(q) almost decomposable
- with VI feasible set C = ∏_{i=0}^N Qⁱ ∩ {q:MC(q) = 0} almost decomposable

What this talk is about?

- Large-scale variational inequalities
 VI(F, C) : ⟨F(q̄), q q̄⟩ ≥ 0 ∀ feasible q = (q⁰,...,q^N)
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 with VI feasible set C = ∏_{i=0}^N Qⁱ ∩ {q : MC(q) = 0} almost decomposable
- + arising in equilibrium models for energy markets
- + Create stochastic versions for VIs that tackle risk aversion
- + Solve such models.

Context: the industry of electricity



Generation

Transmission

Distribution

>90's business model: competitive G + regulated TD

Rationale: fierce G competition of G provides incentive (- costs, + innovation) **Criticism**: it is not clear how fierce competition is ...

This makes important to understand competitive interaction between <u>several</u> G firms seeking to maximize profit, taking into account unique aspects of electricity: not storable, yet supply needs to meet demand, energy needs to be transmitted from G plants to consumers, etc

European NG network

R. Egging, S. A. Gabriel, F. Holtz and J. Zhuang

A complementarity model for the European natural gas marketEnergy Policy, 36:2385–2414, 2008.



Market: Premises

- + Agents (producers, traders, logistics)
 - -take unilateral decisions
 - -behave competitively
- + A representative of the consumers (the ISO)
 - -focuses on the benefits of consumption
 - -seeking a price that matches supply and demand -while keeping prices "low"
- + Agents' actions coupled by some relations, clearing the market.

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Typically, models from game theory or complementarity leading to VIs

Market as a generalized Nash model

+ Agents (producers, traders, logistics)

ith producer problem $\begin{cases} \min c^{i}(q^{i}) \\ s.t. \quad q^{i} \in Q^{i} \\ q^{i} + \sum_{j \neq i} \tilde{q}^{j} = DEM \iff MC(q^{i}, \tilde{q}^{-i}) = 0 \end{cases}$

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$$\begin{array}{l} \text{ith producer problem} \left\{ \begin{array}{ll} \min \ c^{i}(q^{i}) \\ \text{s.t.} \ q^{i} \in Q^{i} \\ q^{i} + \sum_{j \neq i} \tilde{q}^{j} = \text{DEM} \Longleftrightarrow \ \text{MC}(q^{i}, \tilde{q}^{-i}) = 0 \end{array} \right. \\ \left. \begin{array}{l} + \ \text{A representative of the consumers (the ISO)} \\ \text{Agent 0 problem} \left\{ \begin{array}{l} \min \ c^{0}(\tilde{q}^{-0}) \\ \text{s.t.} \ q^{0} = \text{DEM} - \sum_{j \neq 0} \tilde{q}^{j} \in Q^{0} \end{array} \right. \\ \end{array} \right. \end{array}$$

Market as a generalized Nash model

+ Agents (producers, traders, logistics)

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+ A representative of the consumers (the ISO)

Agent 0 problem
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$$\begin{pmatrix} \min c^{i}(q^{i}, \tilde{q}^{-i}) \\ \text{s.t. } q^{i} \in Q^{i} \\ MC(q^{i}, \tilde{q}^{-i}) = 0 \end{cases}$$

Market:Equilibrium price: $\bar{\pi}$

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A Variational Equilibrium of the game is a Generalized Nash Equilibrium satisfying $\bar{\pi}^{i} = \bar{\pi}$

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Market: VI reformulation

Agents problems $\begin{cases} \min & c^{i}(q^{i}, \tilde{q}^{-i}) \\ \text{s.t.} & q^{i} \in Q^{i} \\ & \text{MC}(q^{i}, \tilde{q}^{-i}) = 0 \end{cases}$

Variational Inequality follows from optimality conditions

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1st order OC
(primal form)
$$\left\langle \nabla_{q^{i}} c^{i}(\bar{q}), q^{i} - \bar{q}^{i} \right\rangle \ge 0$$

 $\forall q^{i} \in Q^{i} \cap MC$

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Variational Inequality follows from optimality conditions

In VI(F,C): $\langle F(\bar{q}), q - \bar{q} \rangle \ge 0 \forall$ feasible q

• the VI operator $F(q) = \prod_{i=0}^{N} F^{i}(q)$ for $F^{i}(q) = \nabla_{q^{i}} c^{i}(q)$ • the VI feasible set $C = \prod_{i=0}^{N} Q^{i} \bigcap \{q : MC(q) = 0\}$

NOTE: MC does not depend on i: constraint is **shared**

Application to symmetric electricity market

An ISO wants to design a market, by splitting a set of

 $N_T = 100$ thermal power plants into

 $N = \{1, 2, 3, 4, 5, 10, 25, 50, 75, 100\}$ firms.

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N	1	2	4	5	10	25	50	100
π	20.5	20.5	20.5	20	20	20	20	20
Deficit	5	5	5	0	0	0	0	0

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If less than 4 firms share the market

it behaves like a monopoly,

with bad consequences for consumers: + price, - quality

Suppose there are k = 1, ..., K uncertain scenarios (demand, costs, etc) Production variables depend on realizations: $q_k = (q_k^i, i = 0, ..., N)$

ith problem for scenario k

min
$$c_k^i(q_k^i, q_k^{-i})$$

s.t. $q_k^i \in Q_k^i$
 $MC_k(q_k^i, q_k^{-i}) = 0$

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For one scenario k, a VI(F_k, C_k) with $F_k^i(q_k) = \nabla_{q_k^i} c_k^i(q_k)$

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VI literature treats uncertainty in VI(F_k, C_k) using a gap function, or taking expectation in F: VI($\mathbb{E}\left[(F_k)_{k=1}^K\right], C_k$) same C

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We can do better (VI origin is known)

1st handle uncertainty in agents problems

2nd derive the VI

Stochastic VI for risk-averse agents

Use CVaR risk measure, and derive VI from

ith problem with risk aversion

$$\begin{array}{ll} \min & \text{CVaR}\left[(c_k^i(q_k))_{k=1}^K\right]\\ \text{s.t.} & q_k^i \in Q_k^i \text{ for } k=1:K\\ & \text{MC}_k(q_k)=0 \text{ for } k=1:K \end{array}$$

Difficulties arise:

• As written, CVaR nonsmoothness makes the VI operator $\partial_{q_{1:K}^{i}}$ CVaR $[c^{i}(q)]$, multivalued

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$$CVaR_{\varepsilon}[\boldsymbol{\mathcal{Z}}] = \min_{\boldsymbol{u}} \left\{ \boldsymbol{u} + \frac{1}{1-\varepsilon} \mathbb{E}\left[[\boldsymbol{\mathcal{Z}}_{k} - \boldsymbol{u}]^{+} \right] \right\}$$

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Difficulties arise:

- As written, CVaR nonsmoothness makes the VI operator $\partial_{q_{1:K}^{i}}$ CVaR $[c^{i}(q)]$, multivalued
- Reformulating the agents problem by means of $CVaR_{\varepsilon}[\mathcal{Z}] = min_{u} \left\{ u + \frac{1}{1-\varepsilon} \mathbb{E}\left[[\mathcal{Z}_{k} - u]^{+}\right] \right\}$ couples all scenarios.

CVaR reformulation

$$\begin{split} & \text{FROM} \, \left\{ \begin{array}{ll} \min \quad \text{CVaR} \left[(c_k^i(q_k))_{k=1}^K \right] \\ & \text{s.t.} \quad q_k^i \in Q_k^i \text{ for } k=1: K \quad \text{using} \\ & \text{MC}_k(q_k) = 0 \text{ for } k=1: K, \end{array} \right. \\ & \text{CVaR}[\boldsymbol{\mathcal{Z}}] := \min_u \left\{ u + \frac{1}{1-\epsilon} \mathbb{E} \left[[\boldsymbol{\mathcal{Z}}_k - u]^+ \right] \right\} \text{ and writing } []^+ \text{ by means} \\ & \text{of new variables and constraints} \end{array} \\ & \text{TO:} \left\{ \begin{array}{ll} \min \quad \boldsymbol{u}^i + \frac{1}{1-\epsilon} \mathbb{E} \left[(\boldsymbol{T}_k^i)_{k=1}^K \right] \\ & \text{s.t.} \quad q_k \in Q_k \text{ for } k=1: K \\ & \text{MC}_k(q_k) = 0 \text{ for } k=1: K \\ & \text{T}_k^i \geq c_k^i(q_k) - u^i, T_k^i \geq 0 \text{ for } k=1: K, \boldsymbol{u}^i \in \mathbb{R} \end{array} \right. \end{split} \end{split}$$

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NOTE: new constraint is **NOT shared**

no longer a generalized Nash game, but a bilinear CP (\exists ?).

Dealing with multivalued Risk-Averse VIs

The risk measure $\rho(\boldsymbol{Z}) := CVaR_{\varepsilon}[\boldsymbol{Z}] = min_{u} \left\{ u + \frac{1}{1-\varepsilon}\mathbb{E}\left[[\boldsymbol{Z}_{k} - u]^{+}\right] \right\}$ is nonsmooth because it is a value-function and $[\cdot]^{+}$ is nonsmooth

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We use smooth approximations ρ^{ℓ} $\rho^{\ell}(\boldsymbol{\mathcal{Z}}) := \min_{\boldsymbol{u}} \left\{ \boldsymbol{u} + \frac{1}{1-\varepsilon} \mathbb{E} \left[\boldsymbol{\sigma}_{\ell}(\boldsymbol{\mathcal{Z}}_{k} - \boldsymbol{u}) \right] \right\},$

for smoothing $\sigma_{\ell} \to [\cdot]^+$ uniformly as $\tau_{\ell} \to 0$. For instance,

 $\sigma_{\ell}(t) = (t + \sqrt{t^2 + 4\tau_{\ell}^2})/2$

Since ρ^{ℓ} is smooth, $\mathbf{VI}(F^{\ell}, C)$ has a single-valued VI operator involving $\nabla_{q^i} \rho^{\ell} \left[(c_k^i(q_k))_{k=1}^K \right]$

Theorems

- like CVaR, ρ^{ℓ} is a risk-measure
 - convex, monotone, and translation equi-variant,
 - but not positively homogeneous (only coherent in the limit).
- ρ^{ℓ} is C² for strictly convex smoothings such as $(t + \sqrt{t^2 + 4\tau_{\ell}^2})/2$
- Any accumulation point of the smoothed problems solves the original risk-averse (non-smooth) problem as $\ell \to \infty$.

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existence result

Reference: An approximation scheme for a class of risk-averse stochastic equilibrium problems. Luna, Sagastizábal, Solodov

Assessing both options

+ Smoothed CVaR

Keeps feasible set separable by scenarios: easier VI Needs to drive smoothing parameter to ∞ : repeated VI solving

+ Reformulated CVaR

eliminates nonsmoothness

Non-separable feasible set

Smoothed versus Reformulated CVaR

Random toy problems solved with PATH S. Dirkse, M. C. Ferris, and T. Munson

Time (averaged for 5 instances)
 With K = 20 both formulations take 13 s
 With K = 100, reformulated CVaR takes 100 times longer (smoothing 33 s, reformulation 55 min!)

Smoothed versus Reformulated CVaR

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+ Solution quality (20 runs, K = 50): comparing equilibrium prices and production variables obtained with $\tau \in \{10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 0.2, 0.4, 0.6, 0.8, 1., 10, 50, 75, 100\}$ and with reformulation gives practically identical results for $\tau^{\ell} < 1$.

Final Comments

- When in the agents' problems objective function depends on actions of other agents', writing down the stochastic VI can be tricky: which selection mechanism in a 2-stage setting?
- Handling CVaR nonsmoothness via reformulation seems inadequate for large instances
- Smoothing solves satisfactorily the original risk-averse nonsmooth problem for moderate τ (no need to make $\tau \rightarrow 0$)
- Smoothing preserves separability; it is possible to combine
 - Benders' techniques (along scenarios) with
 - Dantzig-Wolfe decomposition (along agents)
- Decomposition matters: for European Natural Gas network
 - Solving VI directly with PATH solver S. Dirkse, M. C. Ferris, and T. Munson
 - Using DW-decomposition saves 2/3 of solution time

From April to June 2016 IMPA will host

http://svan2016.sciencesconf.org , a thematic trimestre

Stochastic Variational Analysis

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Stochastic Variational Analysis

- Workshop on Analysis and Applications of Stochastic Systems
 - stochastic networks and games;
 - energy markets and financial mathematics, and
 - the optimal control and optimization of systems s. t. uncertainty.
- Basic course on Stochastic Programming and minicourses on
 - Scenario generation and sampling methods
 - Randomized Methods, Machine Learning, Big Data
 - Equilibrium Routing under Uncertainty
 - Stochastic VIs
- ICSP 2016

Plenary talks in

http://icsp2016.sciencesconf.org

- Designing the uncertainty models (J. Royset)
- Risk measures (A. Ruszczynski)
- Mixed integer stochastic programming (S. Ahmed)
- Stochastic programming for energy planning (M. Pereira)

Minisymposia (=1 semiplenary + 3 talks)

- Data-driven methods (G. Bayraksan)
- Stochastic dynamic programming (D. Brown)
- Machine learning and stochastic optimization (W. Powell)
- Stochastic equilibrium and variational inequalities (H. Xu)
- Finance (M. Kopa)
- Applications in natural resources (D. Woodruff)

Tutorials on the weekend before the conference SAVE THE DATES! June 25th-July 1st, 2016



Submission deadlines

Thematic Sessions: June, July, August, 2015 Individual Contributions: September 2015 - January 2016