

Mathematical Program with Equilibrium Constraints (MPEC)

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MPEC model

$$\begin{aligned} \min_z \quad & f(z) \\ \text{s.t.} \quad & g(z) \geq 0, \quad (\text{side inequality}) \\ & h(z) = 0, \quad (\text{side equality}) \\ & 0 \leq r(z) \perp s(z) \geq 0 \quad (\text{complementarity constraint}) \end{aligned}$$

$g : \mathbb{R}^n \rightarrow \mathbb{R}^{m_g}$, $h : \mathbb{R}^n \rightarrow \mathbb{R}^{m_h}$, $r, s : \mathbb{R}^n \rightarrow \mathbb{R}^m$. \perp denotes perpendicularity.

○ also called the Mathematical Program with Complementarity Constraints (MPCC).

Outline

Part 1 Introduction to CP and VI

Part 2 Source problems of VI/CP

Part 3 Source problems of MPEC

Part 4 Solution analysis of MPEC

Part 5 Prevailing algorithm of MPEC

Complementarity Problem (CP)

$$0 \leq r(z) \perp s(z) \geq 0$$

- **LCP:** both sides of \perp are linear functions
- **NCP:** not both sides of \perp are linear

Mixed complementarity problem:

$$0 \leq r_j(z) \perp s_j(z) \geq 0, \forall j \in J \text{ (an index set)}$$

$$\text{free } r_j(z) \perp s_j(z) = 0, \forall j \notin J$$

Variational inequality

Variational Inequality (VI): Given a set K and a function $F : K \rightarrow \mathbb{R}^n$, $VI(K, F) :=$

$$(y - x)^T F(x) \geq 0, \forall y \in K.$$

--> Solve for an x satisfying the above condition.

- **AVI:** If F is affine and K is polyhedral.

Relationship between CP and VI

- ★ CP can be obtained by specializing VI. VI is more general than CP.
- ★ When the set K is a cone, VI can be written as CP.
- ★ VI is a nontrivial extension of a nonlinear program (NLP).

From NLP to VI/CP

Constrained optimization program:

$$\begin{aligned} \min \quad & \theta(x) \\ \text{s.t.} \quad & x \in K \end{aligned}$$

○ If K is convex, a local minimum x^* satisfies

$$(x - x^*)^T \nabla \theta(x) \geq 0, \forall x \in K.$$

--> $VI(K, \nabla \theta)$.

○ **Known result:** At what condition a function, F is the gradient of another function θ , i.e., F is integrable?

— The Jacobian matrix $JF(x)$ is symmetric $\forall x \in$ feasible region.

From VI to NLP

Consider the set K :

$$K \equiv \{x \in R^n : h(x) = 0, g(x) \leq 0\}$$

$$h : R^n \rightarrow R^\ell, g : R^n \rightarrow R^m.$$

If x solves $\text{VI}(K, F)$, then x solves the following NLP

$$\begin{array}{ll} \min & y^T F(x) \\ \text{s.t.} & y \in K \end{array}$$

, i.e., $y^* = x$.

KKT condition

The above NLP has the optimality (necessary) condition:

◦ Assume CQ holds at x , then there exist vectors $\mu \in R^\ell$ and $\lambda \in R^m$ such that

$$0 = F(x) + \sum_{j=1}^{\ell} \mu_j \nabla h_j(x) + \sum_{i=1}^m \nabla g_i(x)$$

$$0 = h(x)$$

$$0 \leq \lambda \perp -g(x) \geq 0.$$

--> A mixed CP in x, μ, λ .

Noncooperative game

A noncooperative game, N players.

- Player i 's strategy set: K_i
- Player i 's strategy: x^i
- Player i 's cost function: $\theta_i(\mathbf{x})$, depends on all players' strategies. \mathbf{x} consists of all subvectors x^i

Noncooperative game/Cooperative game

Given other $N - 1$ players' strategies \mathbf{x}^{-i} , player i 's optimization problem:

$$\begin{aligned} \min \quad & \theta_i(x^i, \mathbf{x}^{-i}) \\ \text{s.t.} \quad & x^i \in K_i. \end{aligned}$$

Nash Equilibrium

The Nash equilibrium is N players' strategies such that no player has the incentive to unilaterally deviate from the current strategy.

Consider convex K_i and convex cost function θ_i .

\mathbf{x} is a Nash equilibrium if and only if \forall individual i ,

$$(y^i - x^i)^T \nabla_{x^i} \theta_i(\mathbf{x}) \geq 0, \quad \forall y^i \in K_i$$

Special case: two-person zero-sum game

$$N = 2, \theta_1(x) = -\theta_2(x).$$

Concatenating individual VIs

Concatenating the gradients

$$\mathbf{F}(\mathbf{x}) \equiv (\nabla_{x^i} \theta_i(\mathbf{x}))_{i=1}^N.$$

and form the Cartesian product

$$\mathbf{K} \equiv \prod_{i=1}^N K_i$$

As a result, \mathbf{x} is a Nash equilibrium iff $\mathbf{x} \equiv (x^i)_{i=1}^N$ solves the VI

$$(\mathbf{y} - \mathbf{x})^T \mathbf{F}(\mathbf{x}) \geq 0, \forall \mathbf{y} \in \mathbf{K}$$

Mixed CP expression of Nash equilibrium

- Suppose set K_i is specified by inequalities and equalities.
- concatenating N KKT systems
- a mixed CP expression of the Nash Equilibrium.

Bimatrix game

Bimatrix game: $\Gamma(A, B)$

- ★ Player I and player II participate.
- ★ A and B are **costs matrices** incurred by players I and II respectively.
- ★ Suppose player I has m strategies and player II has n strategies. $A, B \in R^{m \times n}$.
- ★ Two strategy settings: pure strategy, mixed strategy

- 1. Pure strategies:** When player I chooses strategy i and player II chooses strategy j , player I incurs cost A_{ij} and player II incurs B_{ij} .
- 2. Mixed strategies:** Introduce $x \in R^m$ and $y \in R^n$ the probabilities of choosing each strategy for player I and II respectively. Player I incurs *expected cost* $x^T Ay$ and player II incurs $x^T By$.

Bimatrix game—equilibrium of mixed strategies

A pair of mixed strategies (x^*, y^*) is said to be a **Nash equilibrium** if

$$(x^*)^T A y^* \leq x^T A y^*, \forall x \geq 0 \text{ and } \sum_{i=1}^m x_i = 1$$

$$(x^*)^T B y^* \leq x^{*T} A y, \forall y \geq 0 \text{ and } \sum_{j=1}^n y_j = 1$$

Supply-Demand market equilibrium

1. Supply side:

$$\begin{aligned} \min \quad & c^T x \\ \text{s.t.} \quad & Ax \geq b \\ & Bx \geq r^* \\ & x \geq 0. \end{aligned}$$

c : cost for the supply activities

x : production activity level

$Ax \geq b$: technological constraints

$Bx \geq r^*$: demand requirement constraint

Supply-Demand market equilibrium

2. Demand side:

$$r^* = Q(p^*) = Dp^* + d$$

$Q(\cdot)$: market demand function, assumed affine

p^* : prices

r^* : demand quantities

Supply-Demand market equilibrium

Denote π^* : the shadow price (i.e., the market supply prices) corresponding to the constraint $Bx \geq r^*$

3. Equilibrating condition:

$$p^* = \pi^*$$

Mathematically, we are to find p^* and r^* so that the above 3 things are satisfied.

Supply-Demand market equilibrium—LCP formulation

First we write the optimality condition for supply side, where v is the multiplier corresponding to $Ax \geq b$:

$$0 \leq c - A^T v^* - B^T \pi^* \quad \perp \quad x^* \geq 0$$

$$0 \leq Ax^* - b \quad \perp \quad v^* \geq 0$$

$$0 \leq Bx^* - r^* \quad \perp \quad \pi^* \geq 0$$

Then substitute r^* by $Dp^* + d$ and π^* by p^* . Done.

Cournot production problem

Cournot production problem: The price of goods depends on total quantity in the market.

- quantity competition. (Cournot competition)
- a phenomenon accompanying with oligopoly
- may be reduced to monopoly or extend to perfect competition

Cournot production and distribution problem formulation

Plants are on a network with node set \mathcal{N} and arc set \mathcal{A} .
 M producers. \mathcal{N}_f are markets where firm f has a plant.

Variables:

x_{fa} : amount of flow controlled by f on link a

s_{fi} : amount of the commodity produced by firm f at node i

d_{fj} : amount of the commodity delivered by firm f to node j

Parameters:

$C_{fi}(s_{fi})$: cost to f of producing s_{fi} units of the commodity at i .

CAP_{fi} : capacity of firm f to produce at i .

$c_{fa}(x_{fa})$: cost to f of shipping x_{fa} units on link a .

Total quantity decides price

Denote

$$Q_j = \sum_{f=1}^M d_{fj}$$

The unit price is expressed as

$$p_j(Q_j)$$

Firm f 's profit maximization:

$$\max \theta_f \equiv \sum_{j \in \mathcal{N}} d_{fj} p_j(Q_j) - \sum_{i \in \mathcal{N}_f} C_{fi}(s_{fi}) - \sum_{a \in A} x_{fa} c_a(x_{fa})$$

Optimal production and distribution

Constraints:

$$s_{fi} \leq CAP_{fi}, \quad \forall i \in N_f$$

$$d_{fi} + \sum_{a \in A_i^+} x_{fa} = s_{fi} + \sum_{a \in A_i^-} x_{fa}, \quad \forall i \in \mathcal{N}_f$$

$$d_{fi} + \sum_{a \in A_i^+} x_{fa} = \sum_{a \in A_i^-} x_{fa}, \quad \forall i \in \mathcal{N} \setminus \mathcal{N}_f$$

$$d_{fi}, s_{fi}, x_{fa} \geq 0.$$

A_i^+ : set of arcs with i as the beginning node

A_i^- : set of arcs with i as the ending node.

★ Denote K_f the constraints set containing above constraints.

Nash-Cournot Equilibrium

Let x^f be the stack of variables $[d, s, x]$ and $\mathbf{x} = (x^f)_{f=1}^M$.

★ Rewrite firm f 's optimization problem.

Standard form:

$$\begin{aligned} \max \quad & \theta_f(\mathbf{x}) \\ \text{s.t.} \quad & x^f \in K_f. \end{aligned}$$

Nash-Cournot equilibrium

\mathbf{x} is a equilibrium iff $\mathbf{x} \equiv (x^i)_{i=1}^N$ solves

$$(\mathbf{y} - \mathbf{x})^T \mathbf{F}(\mathbf{x}) \geq 0, \forall \mathbf{y} \in \mathbf{K}$$

where $\mathbf{F}(\mathbf{x})$ be the concatenation of $-\nabla_{x^f} \theta_f(\mathbf{x})$.

Cournot production and distribution—electricity network

Electricity: an oligopoly market — Cournot production

Main aspects:

- generation [**multiple generation plants on a node**]
- transmission [**extra supply through arcs**]
- distribution [**fulfilling demand on each node**]

Electricity market notations

Additional notations needed:

Parameters:

G_{fi} : set of generation plants owned by firm f at node $i \in N_f$

CAP_{fih} : generation capacity at plant $h \in G_{fi}$

CAP_a : transmission capacity on link a

$\rho_a(\mathbf{z})$: transmission price on link a depending on total flow \mathbf{z}

C_{fih} : the cost of generation to firm f at site i and plant h .

Variables:

y_{fih} : amount produced at plant $h \in G_{fi}$

Electricity market notations

Firm f 's profit maximization problem:

$$\begin{aligned} \max \quad & \theta_f(x^f) \\ \text{s.t.} \quad & x^f \in K_f(\mathbf{x}^{-f}) \end{aligned}$$

x^f : firm f 's decision variables including $[d, y, x]$

\mathbf{x}^{-f} : decisions made by firms other than f

$\theta_f(x^f)$: profit of firm f resulting from the decision

$K_f(\mathbf{x}^{-f})$: constraints set of firm f , where some of the parameters are determined by other firms.

Electricity market notations

$$\theta_f(x^f) = \sum_{j \in N} d_{fj} p_j \left(\sum_{g=1}^M d_{gj} \right) - \sum_{i \in N_f} \sum_{h \in G_{fi}} C_{fih}(y_{fih}) - \sum_{a \in A} x_{fa} \rho_a$$

$$K_f(\mathbf{x}^{-f}) \equiv$$

$$y_{fih} \leq CAP_{fih}, \forall h \in G_{fk}, \quad \forall i \in N_f$$

$$d_{fi} + \sum_{a \in A_i^+} x_{fa} = \sum_{h \in G_{fi}} y_{fih} + \sum_{a \in A_i^-} x_{fa}, \quad \forall i \in N_f$$

$$d_{fi} + \sum_{a \in A_i^+} x_{fa} = \sum_{a \in A_i^-} x_{fa}, \quad \forall i \in N \setminus N_f$$

$$\sum_{f' \in F} x_{f'a} \leq CAP_a, \quad \forall a \in A \text{ [link capacity]}$$

$$x_{fa}, y_{fih}, d_{fi} \geq 0.$$

Electricity market notations

Further define $\tilde{K}_f \equiv$

$$y_{fih} \leq CAP_{fih}, \forall h \in G_{fk}, \quad \forall i \in N_f$$

$$d_{fi} + \sum_{a \in A_i^+} x_{fa} = \sum_{h \in G_{fi}} y_{fih} + \sum_{a \in A_i^-} x_{fa}, \quad \forall i \in N_f$$

$$d_{fi} + \sum_{a \in A_i^+} x_{fa} = \sum_{a \in A_i^-} x_{fa}, \quad \forall i \in N \setminus N_f$$

Define

$$K_f(\mathbf{x}) \equiv \{x^f : \sum_{f' \in F} x_{f'a} \leq CAP_a\} \cap \tilde{K}_f$$

$$\Omega \equiv \{\mathbf{x} : \text{all } \mathbf{x} \text{ satisfying link capacity}\}$$

$$\mathbf{K} \equiv \left(\prod_{f=a}^M \tilde{K}_f \right) \cap \Omega$$

Electricity market notations

$$\mathbf{F}(\mathbf{d}, \mathbf{y}, \mathbf{z}) = \begin{pmatrix} -\frac{\partial \theta_f(\mathbf{x})}{\partial d_{fi}} : \forall f, i \\ \frac{dC_{fih}(y_{fih})}{dy_{fih}} : \forall f, i, h \\ \rho.(\mathbf{z}) \otimes e \end{pmatrix}$$

$\rho.$ is the vector of all ρ_a , $a \in A$, \otimes denotes the Kronecker product, and e is the vector of ones in R^M . This produces M copies of $\rho.$

--> Equilibrium $(\mathbf{d}, \mathbf{y}, \mathbf{z})$ are those solve the $VI(\mathbf{K}, \mathbf{F})$.

Structural Estimation

The structural estimation is a (relatively) new-born technique which involves:

1. Assuming a parametric model for the system
 - ▶ including probabilistic assumptions on random quantities
2. Deducing a set of necessary (structural) equations for unknown parameters
 - ▶ including optimality condition of optimization within the system
3. Solving an MPEC corresponding to a generalized method of moment (GMM) estimate of the parameters.
 - ▶ including optimality condition of optimization within the system and the orthogonality conditions of instrumental variables used in GMM

Structural Estimation: pure characteristics

To describe the demand of consumers,

- ▷ Discrete choice, 1974
- ▷ Random Coefficients Logit (or BLP model), 1995
- ▷ Pure Characteristics (or PCM), 2007

In PCM,

the utility for consumer i buying product j in market t is

$$u_{ijt} = \mathbf{x}_{jt}^T \boldsymbol{\beta}_i - \alpha_i p_{jt} + \xi_{jt},$$

$\mathbf{x}_{jt} \in R^K$: observed product characteristics,

p_{jt} : price of product j in market t ,

$\boldsymbol{\beta}_i \in R^K$ and α_i : consumer specific coefficients, and

ξ_{jt} : the only **unobserved** characteristic.

Structural Estimation: pure characteristics

Select the coefficients β_i , α_i and ξ_{jt} so the utility is appropriate.

Structures include market-level observations that should be met:

- ★ Market share (or product quantity sold)
- ★ Distribution of the random coefficients β_i and α_i
- ★ Observed product price
- ★ Distribution of the marginal cost
- ★ Competitive environment --> a Game with $F + 1$ players

Model development

- ▶ Introduce π_{ijt} : probability for consumer i to buy product j in market t .

Rational consumers do the following:

$$0 \leq \pi_{ijt} \quad \perp \quad \gamma_{it} - [\mathbf{x}_{jt}^T \boldsymbol{\beta}_i - \alpha_i p_{jt} + \xi_{jt}] \geq 0$$

$$0 \leq \gamma_{it} \quad \perp \quad \pi_{i0t} = 1 - \sum_{j=1}^J \pi_{ijt} \geq 0,$$

$$\text{where } \gamma_{it} = \max \left\{ 0, \max_{1 \leq l \leq J} (\mathbf{x}_{lt}^T \boldsymbol{\beta}_i - \alpha_i p_{lt} + \xi_{lt}) \right\}.$$

Model development

- ▶ The $F + 1$ players in the Game are F firms and a virtual league of consumers.
 - ★ F firms: pricing problem
 - ★ The league of consumers: maximizing the aggregated utility, also called “market optimization” problem.
- ▶ Use Generalized Method of Moments (GMM) for minimizing residuals.

The estimation model

QPNCC_{EsP,NB}($\mathbf{Z}_\xi; \Lambda_\xi; \mathbf{Z}_\omega; \Lambda_\omega; \mathcal{M}_t; N; q; p^{obs}; x; y; \eta; w; \mathbf{z}$):

$$\min_{\theta \in \Upsilon; mc; \xi; \omega; \mathbf{z}} \quad \frac{1}{2} \boldsymbol{\xi}^T \mathbf{Z}_\xi \Lambda_\xi \mathbf{Z}_\xi^T \boldsymbol{\xi} + \frac{1}{2} \boldsymbol{\omega}^T \mathbf{Z}_\omega \Lambda_\omega \mathbf{Z}_\omega^T \boldsymbol{\omega}$$

subject to $\bullet \forall t = 1, \dots, T, j = 1, \dots, J$, and $f = 1, \dots, F$:

$$\frac{\mathcal{M}_t}{N} \sum_{i=1}^N \pi_{ijt} = q_{jt}; \quad \hat{p}_{jt} = p_{jt}^{obs} - mc_{jt}$$

$\bullet \forall t = 1, \dots, T; i = 1, \dots, N$; and $j = 1, \dots, J$:

complementarities in the Nash-Bertrand Game

$$\bullet 0 \leq mc_{jt} \leq p_{jt}^{obs}$$

$$\bullet \beta_{ik} = \bar{\beta}_k + \sigma_{\beta k} \eta_{ik} \quad \forall k = 1, \dots, K,$$

$$\bullet \alpha_i = \exp(\bar{\alpha} w_i)$$

and

$$\bullet mc_{jt} = \mathbf{y}_{jt}^T \boldsymbol{\phi} + \omega_{jt}.$$

Appendix: The Nash-Bertrand game

$$0 \leq v_{ijt} \quad \perp \quad \frac{\mathcal{M}_t}{N} \pi_{ijt} - \sum_{\ell=1}^J \lambda_{ij\ell t} \geq 0,$$

$$\forall i = 1, \dots, N; j = 1, \dots, J; t = 1, \dots, T$$

$$0 \leq \hat{p}_{jt} \quad \perp \quad - \sum_{i=1}^N \sum_{j' \in J_f} \lambda_{ij'jt} \geq 0,$$

$$\forall j = 1, \dots, J; t = 1, \dots, T$$

$$0 \leq \lambda_{ij\ell t} \quad \perp \quad v_{ij\ell t} + \hat{p}_{\ell t} - \frac{\mathbf{x}_{\ell t}^T \boldsymbol{\beta}_i - \alpha_i mc_{jt} + \xi_{\ell t}}{\alpha_i} \geq 0,$$

$$\forall i = 1, \dots, N; j = 1, \dots, J; \ell = 1, \dots, J; t = 1, \dots, T$$

$$0 \leq \pi_{ijt} \quad \perp \quad \gamma_{it} + \alpha_i \hat{p}_{jt} - (\mathbf{x}_{jt}^T \boldsymbol{\beta}_i - \alpha_i mc_{jt} + \xi_{jt}) \geq 0,$$

$$\forall i = 1, \dots, N; j = 1, \dots, J; t = 1, \dots, T$$

$$0 \leq \gamma_{it} \quad \perp \quad 1 - \sum_{j=1}^J \pi_{ijt} \geq 0.$$

$$\forall i = 1, \dots, N; t = 1, \dots, T$$

MPEC as an extension of NLP

Problematic! The existence of Lagrange multipliers is not guaranteed.

Resolution: MPEC stationary conditions and MPEC constraint qualification

- We will use the MPEC formulation (on p.2) but eliminate the side equality constraint for the following definitions.

Definition: For a feasible point z , the *MPEC-active set* is given by the active constraint indices

$$I_g(z) = \{i : g_i(z) = 0\}$$

$$I_r(z) = \{i : r_i(z) = 0\}$$

$$I_s(z) = \{i : s_i(z) = 0\}$$

MPEC stationarity

Definition: Let z be feasible for MPEC. We say z is *B-stationary* or *primal stationary* if for each partition $I \cup J$ of $\{1, \dots, m\}$ such that $I \supset I_r(z)$ and $J \supset I_s(z)$, z is stationary for $(NLP(I))$:

$$\begin{aligned} \min_z \quad & f(z) \\ \text{s.t.} \quad & g(z) \geq 0 \\ & r_I(z) = 0 \leq s_I(z) \\ & r_J(z) \geq 0 = s_J(z) \end{aligned}$$

Note: Other MPEC-stationarity includes strong-stationarity, weak-stationarity, C-stationary and A-stationarity.

Definition: Let z be feasible for the MPEC. The *MPEC-LICQ* holds at z if the MPEC-active constraint gradients

$$\{\nabla_z g_i(z) : i \in I_g(z)\} \cup \{\nabla_x r_i(z) : i \in I_r(z)\} \cup \{\nabla_z s_i(z) : i \in I_s(z)\}$$

are linearly independent.

Equivalent NLP

$$\begin{aligned} \min_z \quad & f(z) \\ \text{s.t.} \quad & g(z) \geq 0 \\ & r(z), s(z) \geq 0 \\ & r(z)^T s(z) \leq 0. \end{aligned}$$

Proposition: Let z^* be feasible for the MPEC at which MPEC-LICQ holds. If z^* is a local minimum of the equivalent NLP, then z^* is a local minimum of the MPEC, z^* is a stationary point of the equivalent NLP, and the KKT multipliers exist for the equivalent NLP.

Note: Similar results can be obtained for formulation of $r(z)^T s(z) = 0$, $r_i(z)s_i(z) = 0, \forall i$, and $r_i(z)s_i(z) \leq 0, \forall i$.

Algorithms for solving MPEC

Methods extended from NLP:

- **SQP-Filter** code (Fletcher and Leyffer)

Methods for solving CP:

- **PATH** solver (Dirkse, Ferris, and Munson): a generalization of Newton's method
- Lemke's method: tableau pivotal

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