

# The Cone Condition and Nonsmoothness in Linear Generalized Nash Games

Oliver Stein

Institute of Operations Research  
Karlsruhe Institute of Technology (KIT)

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This is joint work with

Nathan Sudermann-Merx, Advanced Business Analytics, BASF

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# Survey

- 1 Introduction to GNEPs
  - Setting and definitions
  - An equivalent single optimization problem
  - Smoothness results for player convex problems
- 2 Smoothness results for LGNEPs
  - A global extension of  $V$
  - The cone condition
  - Numerical consequences
  - The common KKT polyhedron and SMFC
- 3 Future research

# GNEPs in the general nonlinear setting

## Given:

- $N$  players  $\nu \in \{1, \dots, N\}$  with decision variables  $x^\nu \in \mathbb{R}^{n_\nu}$ ,
- $x = (x^1, \dots, x^N) = (x^\nu, x^{-\nu}) \in \mathbb{R}^n$  decision vector of all players,
- player  $\nu$ 's cost function  $\theta_\nu(x^\nu, x^{-\nu})$ ,
- player  $\nu$ 's strategy space (= feasible set)

$$X_\nu(x^{-\nu}) = \{x^\nu \in \mathbb{R}^{n_\nu} \mid g^\nu(x^\nu, x^{-\nu}) \leq 0\},$$

## Generalized Nash equilibrium problem

- player  $\nu$ 's optimization problem

$$Q_\nu(x^{-\nu}) : \min_{x^\nu} \theta_\nu(x^\nu, x^{-\nu}) \quad \text{s.t.} \quad g^\nu(x^\nu, x^{-\nu}) \leq 0,$$

- player  $\nu$ 's optimal point set  $S_\nu(x^{-\nu})$ .

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## Literature review

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## Stylized example

Let two players share the constraints

$$g^1(x) = g^2(x) = \begin{pmatrix} -\frac{1}{2} \\ 1 \\ -1 \end{pmatrix} x_1 + \begin{pmatrix} 1 \\ -1 \\ -1 \end{pmatrix} x_2 - \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \leq 0$$

and minimize  $\theta_1(x_1) = -x_1$  and  $\theta_2(x_2) = x_2$ , respectively.

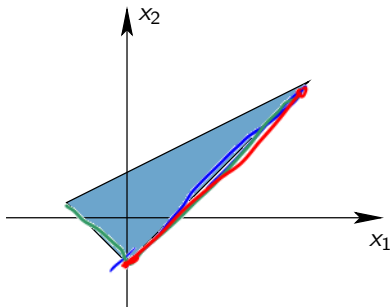


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## Restrictions on $x$

As  $X_\nu(x^{-\nu})$  may be void for some choices of  $x^{-\nu}$ , it makes sense to restrict  $x$  to certain subsets of  $\mathbb{R}^n$ :

For

$$\Omega(x) = X_1(x^{-1}) \times \dots \times X_N(x^{-N})$$

we call

$$M := \text{dom } \Omega = \{x \in \mathbb{R}^n \mid \Omega(x) \neq \emptyset\}$$

the **common consistency set** of all players.

Moreover

$$W := \{x \in \mathbb{R}^n \mid g^\nu(x) \leq 0, \nu = 1, \dots, N\} = \text{fix } \Omega \subseteq \text{dom } \Omega = M$$

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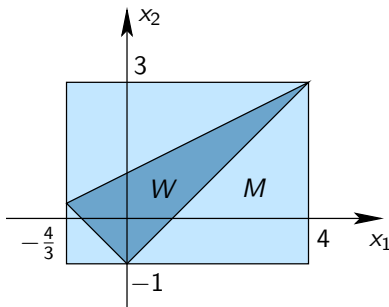
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## Optimal value functions and gap function

With the **players' optimal value functions**

$$\varphi_\nu(x^{-\nu}) := \inf_{x^\nu \in X_\nu(x^{-\nu})} \theta_\nu(x^\nu, x^{-\nu}), \quad \nu = 1, \dots, N,$$

the extended real-valued function

$$V(x) := \sum_{\nu=1}^N (\theta_\nu(x^\nu, x^{-\nu}) - \varphi_\nu(x^{-\nu}))$$

is called **gap function** of the GNEP.

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$$\Rightarrow \varphi_1(x_2) = \begin{cases} -x_2 - 1 & , x_2 \in \text{dom } X_1 = [-1, 3] \\ \infty & , \text{else} \end{cases}$$

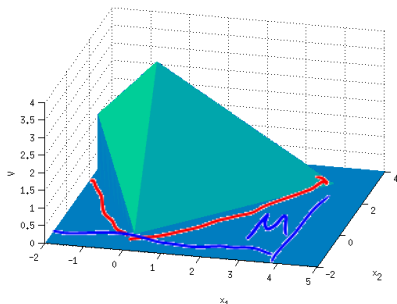
$$\varphi_2(x_1) = \begin{cases} |x_1| - 1 & , x_1 \in \text{dom } X_2 = [-\frac{4}{3}, 4] \\ \infty & , \text{else,} \end{cases}$$

$$V(x) = \begin{cases} 2 - x_1 - |x_1| + 2x_2 & , x \in M = [-\frac{4}{3}, 4] \times [-1, 3] \\ -\infty & , \text{else.} \end{cases}$$

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## Reformulation as a single optimization problem

**Assumption:** For each  $x \in M$  and each  $\nu \in \{1, \dots, N\}$  the problem  $Q^\nu(x^{-\nu})$  is solvable.

Then  $V$  is real-valued on  $M \subseteq W$ .

Theorem (v.Heusinger/Kanzow 2009, Dreves/Kanzow/St. 2012)

*Generalized Nash equilibria are exactly the globally minimal points of the problem*

$$\min V(x) \quad \text{s.t.} \quad x \in W$$

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# Convexity and linearity assumptions

A GNEP is called

- **player convex** if for each  $\nu$  and each  $x^{-\nu}$  the function  $\theta_\nu(\cdot, x^{-\nu})$  and all entries of  $g^\nu(\cdot, x^{-\nu})$  are convex,
- **jointly convex** if for each  $\nu$  the function  $\theta_\nu$  and all entries of  $g^\nu$  are convex,
- **player linear** if for each  $\nu$  and each  $x^{-\nu}$  the functions  $\theta_\nu(\cdot, x^{-\nu})$  and  $g^\nu(\cdot, x^{-\nu})$  are linear,
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## Continuity of $V$ on $W$ for player convex problems

For

$$\Omega(x) = X_1(x^{-1}) \times \dots \times X_N(x^{-N})$$

we call

$$\text{slater } \Omega = \{x \in \mathbb{R}^n \mid \Omega(x) \text{ satisfies the Slater condition}\}$$

the **common Slater set** of all players. Clearly,  $\text{slater } \Omega \subseteq M$ .

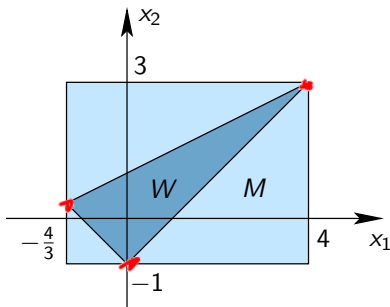
**Theorem (Dreves/Kanzow/St. 2012)**

*For each  $x \in D = W \setminus \text{slater } \Omega$  and each  $\nu \in \{1, \dots, N\}$  such that  $X_\nu(x^{-\nu})$  violates the Slater condition, let  $X_\nu(x^{-\nu}) = \{x^\nu\}$ . Then  $V$  is continuous on  $W$ .*

## Stylized example

$$\theta_1(x_1) = -x_1, \quad \theta_2(x_2) = x_2,$$

$$g^1(x) = g^2(x) = \begin{pmatrix} -\frac{1}{2} \\ 1 \\ -1 \end{pmatrix} x_1 + \begin{pmatrix} 1 \\ -1 \\ -1 \end{pmatrix} x_2 - \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$



## Directional differentiability of $V$ for player convex problems

### Proposition (Harms/Kanzow/St. 2015)

$V$  is Hadamard directionally differentiable at each  $x \in W \setminus D$  with

$$V'(x, d) = \sum_{\nu=1}^N \left[ \langle \nabla \theta_{\nu}(x), d \rangle - \max_{\gamma^{\nu} \in \text{KKT}_{\nu}(x)} \langle \nabla_x L_{\nu}(x, y^{\nu}(x), \gamma^{\nu}), d \rangle \right]$$

for all  $d \in \mathbb{R}^n$ .

Furthermore, in a certain sense the set of nondifferentiability points of  $V$  on  $W$  is small.

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## Linear generalized Nash games

Next we consider completely linear GNEPs (**LGNEPs**):

For each  $\nu \in \{1, \dots, N\}$  and  $x \in \mathbb{R}^n$  let

$$Q_\nu(x^{-\nu}) : \min_{x^\nu \in \mathbb{R}^{n_\nu}} \langle a^\nu, x^\nu \rangle \quad \text{s.t.} \quad A^\nu x^\nu + B^\nu x^{-\nu} \leq c^\nu,$$

that is,

$$\theta_\nu(x^\nu, x^{-\nu}) = \langle a^\nu, x^\nu \rangle \quad (+f(x^{-\nu}))$$

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# Applications

Applications: all linearly coupled LPs, like

- transportation problems with several forwarders (St./Sudermann-Merx 2018)
- linearly modelled profit centers
- routing in telecommunication or traffic networks
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Closest setting in the literature:

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## A global extension of $V$

For all  $\nu = 1, \dots, N$  and  $x^{-\nu} \in \text{dom } X_\nu$  strong duality yields

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$(\text{dom } X_\nu)^c \neq \emptyset \Rightarrow Z_\nu$  unbounded.

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Hence, with the non-empty vertex set

$$O_\nu := \text{vert}(Z_\nu)$$

we may define the global extension

$$\hat{\varphi}_\nu(x^{-\nu}) := \max_{\sigma^\nu \in O_\nu} \langle \sigma^\nu, B^\nu x^{-\nu} - c^\nu \rangle$$

of  $\varphi_\nu$  on  $\mathbb{R}^{n-n_\nu}$  as well as the global extension

$$\hat{V}(x) := \sum_{\nu=1}^N \langle a^\nu, x^\nu \rangle - \hat{\varphi}_\nu(x^{-\nu})$$

of  $V$  on  $\mathbb{R}^n$ .

$\hat{V}$  is **polyhedral and concave** on  $\mathbb{R}^n$  and, hence, so is  $V$  on  $W$ .



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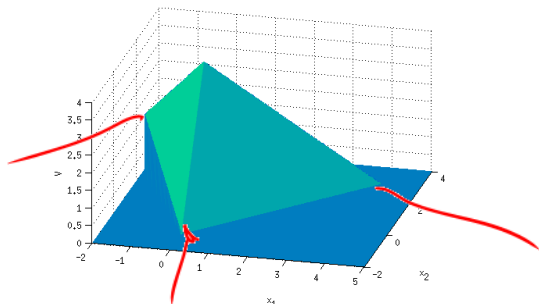
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## Localization and relation to the KKT set

For any  $\nu = 1, \dots, N$  and  $x^{-\nu} \in \mathbb{R}^{n-n_\nu}$  let us define the active set

$$O_\nu(x^{-\nu}) := \{\sigma^\nu \in O_\nu \mid \langle \sigma^\nu, B^\nu x^{-\nu} - c^\nu \rangle = \widehat{\varphi}_\nu(x^{-\nu})\}.$$

Proposition (St./Sudermann-Merx 2016)

Around any  $\bar{x} \in \mathbb{R}^n$  the function  $\widehat{V}$  locally coincides with

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For any  $\nu = 1, \dots, N$  and  $\bar{x}^{-\nu} \in \text{dom } X_\nu$  we have

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## Localization and relation to the KKT set

For any  $\nu = 1, \dots, N$  and  $x^{-\nu} \in \mathbb{R}^{n-n_\nu}$  let us define the active set

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# The cone condition

## Definition

For  $\nu \in \{1, \dots, N\}$  and  $x^{-\nu} \in \mathbb{R}^{n-n_\nu}$  we say that the **player cone condition (PCC)** is valid in  $x^{-\nu}$ , if  $O_\nu(x^{-\nu})$  contains at most one element. We say that the **collective cone condition (CCC)** holds in  $x \in \mathbb{R}^n$ , if PCC holds in  $x^{-\nu}$  for all  $\nu \in \{1, \dots, N\}$ .

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## Theorem (St./Sudermann-Merx 2016)

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## Stylized example

$$\theta_1(x_1) = -x_1, \quad \theta_2(x_2) = x_2,$$

$$g^1(x) = g^2(x) = \begin{pmatrix} -\frac{1}{2} \\ 1 \\ -1 \end{pmatrix} x_1 + \begin{pmatrix} 1 \\ -1 \\ -1 \end{pmatrix} x_2 - \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

$$\Rightarrow Z_1 = \left\{ \sigma^1 \in \mathbb{R}^3 : -1 - \frac{\sigma_1^1}{2} + \sigma_2^1 - \sigma_3^1 = 0, \sigma^1 \geq 0 \right\}$$

$$O_1 = \{(0, 1, 0)^\top\}$$

$$|O_1(x_2)| = 1 \text{ for all } x_2 \in \mathbb{R}$$

$$Z_2 = \left\{ \sigma^2 \in \mathbb{R}^3 : 1 + \sigma_1^2 - \sigma_2^2 - \sigma_3^2 = 0, \sigma^2 \geq 0 \right\}$$

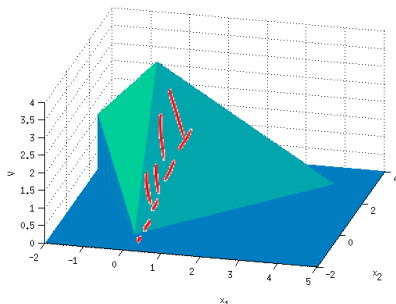
$$O_2 = \{(0, 1, 0)^\top, (0, 0, 1)^\top\}$$

$$|O_2(x_1)| = 1 \Leftrightarrow x_1 \neq 0.$$

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## Characterization of smoothness by the cone condition

### Theorem (St./Sudermann-Merx 2016)

For any  $\nu \in \{1, \dots, N\}$  and  $J \subseteq \{1, \dots, m_\nu\}$  with  $|J| \leq n_\nu$  let the rows  $(A_j^\nu, B_j^\nu)$ ,  $j \in J$ , be linearly independent.

Then  $\widehat{V}$  is smooth at  $\bar{x} \in \mathbb{R}^n$  if and only if CCC holds at  $\bar{x}$ .

For  $n_\nu = 1$ ,  $\nu = 1, \dots, N$ , the above assumption can always be satisfied, otherwise it holds generically.

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## Numerical consequences

Since the nonsmoothness structure of  $\widehat{V}$  is well understood, and in particular, its Clarke subdifferential

$$\partial\widehat{V}(\bar{x}) = \sum_{\nu=1}^N \left\{ (a^\nu, -b^{-\nu}), b^{-\nu} \in \text{conv}\{(B^\nu)^T \sigma^\nu, \sigma^\nu \in O_\nu(\bar{x}^{-\nu})\} \right\}$$

is easily evaluated, LGNEPs may be solved by nonsmooth optimization methods.

## Numerical consequences

An exact penalty method as well as a projected subgradient method were successfully tested by Dreves/Sudermann-Merx 2016 as well as St./Sudermann-Merx 2018.

For example, the projected subgradient method solves LGNEPs with 100 players à 100 variables, that is, a nonsmooth nonconvex optimization problem with 10,000 variables, in about 2 minutes.

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## Common KKT polyhedron

For  $x \in \mathbb{R}^n$  we define the **common KKT polyhedron**

$$\Psi(x) := \text{KKT}_1(x^{-1}) \times \dots \times \text{KKT}_N(x^{-N}).$$

### Lemma

- $x \in M \Leftrightarrow \Psi(x) \neq \emptyset$ .
- $x \in \text{slater } \Omega \Leftrightarrow \Psi(x)$  is bounded.
- If  $W$  possesses a Slater point, then  $\text{slater } \Omega = \text{int } M$ .



# SMFC

## Definition

For  $\nu \in \{1, \dots, N\}$  and  $x^{-\nu} \in \text{dom } X_\nu$ , the **player strict Mangasarian-Fromovitz condition (PSMFC)** is valid in  $x^{-\nu}$ , iff  $|\text{KKT}_\nu(x^{-\nu})| \leq 1$ . The **collective strict Mangasarian-Fromovitz condition (CSMFC)** holds in  $x \in M$ , if PSMFC holds in  $x^{-\nu}$  for all  $\nu \in \{1, \dots, N\}$ .

## Lemma

CSMFC holds at  $x \in M$  iff  $|\Psi(x)| = 1$ .

## Proposition

Let  $W$  possess a Slater point. Then on  $\text{int } M$  the CCC and the CSMFC are equivalent.

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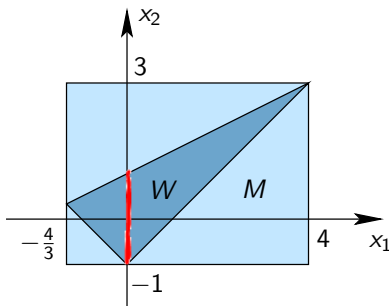
## Proposition

Let  $W$  possess a Slater point. Then on  $\text{int } M$  the CCC and the CSMFC are equivalent.

## Common KKT polyhedron

### Corollary

Let  $W$  possess a Slater point and let CCC be violated at  $\bar{x} \in \text{int } M$ . Then for each  $\nu \in \{1, \dots, N\}$  with  $|\text{KKT}_\nu(\bar{x}^{-\nu})| > 1$  CCC also is violated at each  $x \in \text{int } M$  with  $x^{-\nu} = \bar{x}^{-\nu}$ .



## Future research

- Effects of shared constraints.
- Extension to more general settings (e.g., jointly convex and separable GNEPs).
- Impact of the cone condition in different settings.
- Benders type cutting plane approaches.

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## Reformulation as a single optimization problem

Let  $\varphi_\nu(x^{-\nu}) = \inf_{x^\nu \in X_\nu(x^{-\nu})} \theta_\nu(x^\nu, x^{-\nu}), \quad \nu = 1, \dots, N.$

Then:

$$\begin{aligned}
 x \in \bigcap_{\nu=1}^N \text{gph } S_\nu &\Leftrightarrow x^\nu \in X_\nu(x^{-\nu}), \quad \theta_\nu(x^\nu, x^{-\nu}) = \varphi_\nu(x^{-\nu}) \quad \forall \nu \\
 &\Leftrightarrow x \in \Omega(x), \quad \sum_{\nu=1}^N (\theta_\nu(x^\nu, x^{-\nu}) - \varphi_\nu(x^{-\nu})) = 0 \\
 &\Leftrightarrow x \in W, \quad V(x) = 0 \\
 &\Leftrightarrow x \text{ is minimal point of } V \text{ on } W \\
 &\quad \text{with minimal value } 0.
 \end{aligned}$$

# Nikaido-Isoda function

We have

$$\begin{aligned}
 V(x) &= \sum_{\nu=1}^N (\theta_{\nu}(x^{\nu}, x^{-\nu}) - \varphi_{\nu}(x^{-\nu})) \\
 &= \sum_{\nu=1}^N (\theta_{\nu}(x^{\nu}, x^{-\nu}) - \min_{y^{\nu} \in X_{\nu}(x^{-\nu})} \theta_{\nu}(y^{\nu}, x^{-\nu})) \\
 &= \max_{y \in \Omega(x)} \sum_{\nu=1}^N (\theta_{\nu}(x^{\nu}, x^{-\nu}) - \theta_{\nu}(y^{\nu}, x^{-\nu})).
 \end{aligned}$$

$$\psi(x, y) := \sum_{\nu=1}^N (\theta_{\nu}(x^{\nu}, x^{-\nu}) - \theta_{\nu}(y^{\nu}, x^{-\nu}))$$

is called **Nikaido-Isoda function**.