Mathematical Programs with Complementarity Constraints and Related Problems

TECHNISCHE UNIVERSITÄT DARMSTADT

Prof. Dr. Alexandra Schwartz schwartz@gsc.tu-darmstadt.de



Ressources



You can find

- my slides
- and some more extensive lecture notes

at

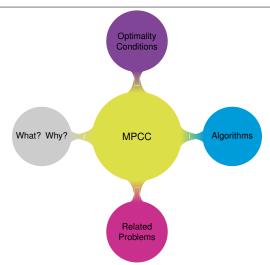
github.com/alexandrabschwartz/Winterschool2018

If you have any questions, please come to me during the week or contact me at schwartz@gsc.tu-darmstadt.de



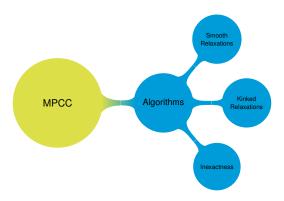
Contents of the Course





What did we do yesterday?

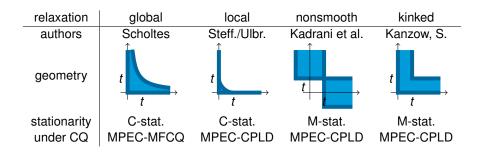






Relaxation Methods: Exact KKT Points





Relaxation Methods: Inexact KKT Points

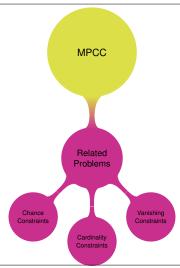


Let $t_k \downarrow 0$ and $\varepsilon_k = o(t_k)$. Let x^k be ε_k -KKT points of NLP(t_k) and assume $x^k \to x^*$. Then the limit x^* satisfies:

relaxation	global	local	nonsmooth	kinked
authors	Scholtes	Steff./Ulbr.	Kadrani et al.	Kanzow, S.
geometry	t t	t t		t t
stationarity	C-stat.	W-stat.	W-stat.	W-stat.
under CQ	MPEC-MFCQ	MPEC-MFCQ	MPEC-MFCQ	MPEC-MFCQ

What is the plan for today?







Vanishing Constraints

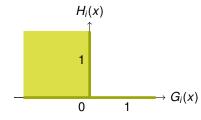
Mathematical Program with Vanishing Constraints (MPVC)



A mathematical program with vanishing constraints (MPVC) is of the form

$$\min_{x} f(x) \quad \text{s.t.} \quad g(x) \le 0, \quad h(x) = 0,$$

$$H(x) \ge 0, \quad G(x) \circ H(x) \ge 0.$$



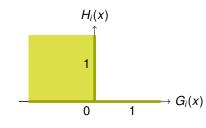
Mathematical Program with Vanishing Constraints (MPVC)



A mathematical program with vanishing constraints (MPVC) is of the form

$$\min_{x} f(x) \quad \text{s.t.} \quad g(x) \le 0, \quad h(x) = 0,$$

$$H(x) \ge 0, \quad G(x) \circ H(x) \ge 0.$$

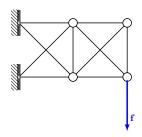


Two cases are possible:

- ► $H_i(x^*) > 0$ and thus $G_i(x^*) \le 0$
- ► $H_i(x^*) = 0$ and then $G_i(x^*) \in \mathbb{R}$ arbitrarily.

Example: Truss Design





Given some anchor points and a load point, how should you construct a load bearing truss?

Example: Truss Design (continued)



$$\begin{aligned} \min_{a,u} & \sum_{i} I_{i} a_{i} \\ \text{s.t.} & 0 \leq a \leq a_{\text{max}} \\ & K(a) u = f \\ & f^{T} u \leq c \\ & (\sigma_{i}(u)^{2} - \sigma_{\text{max}}^{2}) a_{i} \leq 0 \end{aligned}$$

minimize volume of the truss bounds on cross sections force equilibrium bound on the deformation bound on the stress on bar *i*

Variables

- a_i cross sectional area of bar i
- u_i nodal displacements at the hinges

Constants

- f applied force
- Ii length of bar i
- K(a) stiffness matrix of the truss
- $\sigma_i(u)$ stress on bar i

Relation between Vanishing and Complementarity Constraints



One can reformulate an MPVC as an MPCC using slack variables as follows:

$$\min_{x,y} f(x) \quad \text{s.t.} \quad g(x) \le 0, h(x) = 0,$$

$$G(x) - y \le 0,$$

$$0 \le H(x) \perp y \ge 0.$$

Relation between Vanishing and Complementarity Constraints



One can reformulate an MPVC as an MPCC using slack variables as follows:

$$\min_{x,y} f(x) \quad \text{s.t.} \quad g(x) \le 0, h(x) = 0,$$

$$G(x) - y \le 0,$$

$$0 \le H(x) \perp y \ge 0.$$

Exercise

How is the relation between the MPCC reformulation and the original MPVC?





Relation between Vanishing and Complementarity Constraints



One can reformulate an MPVC as an MPCC using slack variables as follows:

$$\min_{x,y} f(x) \quad \text{s.t.} \quad g(x) \le 0, h(x) = 0,$$

$$G(x) - y \le 0,$$

$$0 \le H(x) \perp y \ge 0.$$

Then x^* is a solution of the MPVC if and only if (x^*, y^*) with

$$y_i^* \begin{cases} = 0 & \text{if } H_i(x^*) > 0, \\ \ge \max\{0, G_i(x^*)\} & \text{if } H_i(x^*) = 0 \end{cases}$$

if a solution of the corresponding MPCC. But y^* is not uniquely determined.

MPVCs versus Constraint Qualifications

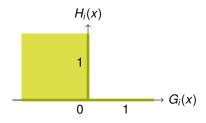


Vanishing Constraints:

$$H(x)_i \geq 0$$
, $G(x)_i H(x)_i \geq 0$ $\forall i = 1, ..., q$

Let x^* be feasible for MPVC.

- If H_i(x*) = 0 for at least one index i ∈ {1,..., q}, then LICQ is violated in x*.
- ▶ If there exists an index i such that $H_i(x^*) = 0$ and $G_i(x^*) \ge 0$, then MFCQ is violated in x^* .
- ► The vanishing constraints *i* with $H_i(x^*) > 0$ are "well-behaved".





One can try to apply NLP theory.





- One can try to apply NLP theory.
- One can use the MPCC reformulation.



- One can try to apply NLP theory.
- One can use the MPCC reformulation.
- ▶ One can define $V := \{(a, b) \in \mathbb{R}^2 \mid b \ge 0, ab \le 0\}$ and use the condition

$$(\gamma_i,\nu_i)\in \textit{N}^{\textit{F}}_{\textit{V}}(\textit{G}_i(\textit{x}^*),\textit{H}_i(\textit{x}^*))\subseteq \textit{N}^{\textit{M}}_{\textit{V}}(\textit{G}_i(\textit{x}^*),\textit{H}_i(\textit{x}^*))$$

to obtain possible optimality conditions.





- One can try to apply NLP theory.
- One can use the MPCC reformulation.
- ▶ One can define $V := \{(a, b) \in \mathbb{R}^2 \mid b \ge 0, ab \le 0\}$ and use the condition

$$(\gamma_i,\nu_i)\in \textit{N}^{\textit{F}}_{\textit{V}}(\textit{G}_i(\textit{x}^*),\textit{H}_i(\textit{x}^*))\subseteq \textit{N}^{\textit{M}}_{\textit{V}}(\textit{G}_i(\textit{x}^*),\textit{H}_i(\textit{x}^*))$$

to obtain possible optimality conditions.

▶ One can locally decompose the MPVC into TNLP(x^* , I) for all $I \subset \{i \mid G_i(x^*) = H_i(x^*) = 0\}$

$$\min_{x} f(x) \quad \text{s.t.} \quad g(x) \le 0, \quad h(x) = 0,$$

$$G_{i}(x) \le 0, \quad H_{i}(x) \ge 0 \quad \forall i \in \{i \mid G_{i}(x^{*}) < 0\} \cup I,$$

$$H_{i}(x) = 0 \quad \forall i \in \{i \mid G_{i}(x^{*}) > 0\} \cup I^{c}$$



- One can try to apply NLP theory.
- One can use the MPCC reformulation.
- ▶ One can define $V := \{(a, b) \in \mathbb{R}^2 \mid b \ge 0, ab \le 0\}$ and use the condition

$$(\gamma_i,\nu_i)\in \textit{N}^{\textit{F}}_{\textit{V}}(\textit{G}_i(\textit{x}^*),\textit{H}_i(\textit{x}^*))\subseteq \textit{N}^{\textit{M}}_{\textit{V}}(\textit{G}_i(\textit{x}^*),\textit{H}_i(\textit{x}^*))$$

to obtain possible optimality conditions.

▶ One can locally decompose the MPVC into TNLP(x^* , I) for all $I \subseteq \{i \mid G_i(x^*) = H_i(x^*) = 0\}$

$$\min_{x} f(x) \quad \text{s.t.} \quad g(x) \le 0, \quad h(x) = 0,$$

$$G_{i}(x) \le 0, \quad H_{i}(x) \ge 0 \quad \forall i \in \{i \mid G_{i}(x^{*}) < 0\} \cup I,$$

$$H_{i}(x) = 0 \quad \forall i \in \{i \mid G_{i}(x^{*}) > 0\} \cup I^{c}$$

One can use a nonsmooth reformulation

$$\varphi(a, b) = \max\{-b, \min\{a, b\}\} < 0.$$



Cardinality Constraints

Cardinality Constrained Optimization Problems



► A cardinality constrained problem is of the form

$$\min_{x} f(x) \quad \text{s.t.} \quad g(x) \le 0, \quad h(x) = 0, \quad \|x\|_{0} \le \kappa$$

with the "sparsity"-term

 $||x||_0 :=$ number of nonzero components of x.

- These problems appear e.g. in
 - portfolio optimization,
 - compressed sensing,
 - feature selection.
 - communications engineering,
 - truss design.



Example: Portfolio Optimization



Consider a basic portfolio selection problem

$$\min_{x} x^{T} Q x \quad \text{s.t.} \quad \mu^{T} x \geq \rho,$$

$$e^{T} x = 1,$$

$$0 \leq x_{i} \leq u_{i} \quad \forall i = 1, \dots, n,$$

$$\|x\|_{0} \leq \kappa,$$

where

- Q is the covariance matrix of the n possible assets,
- \blacktriangleright μ is the expected revenue,
- $e = (1, ..., 1)^T$.

Relation to Sparse Optimization Problems



For some weight $\rho > 0$ consider

$$\min_{x} f(x) + \rho ||x||_{0}$$
 s.t. $g(x) \le 0$, $h(x) = 0$.

Relation to Sparse Optimization Problems



For some weight $\rho > 0$ consider

$$\min_{x} f(x) + \rho ||x||_{0}$$
 s.t. $g(x) \le 0$, $h(x) = 0$.

▶ Sparse → Cardinality: A solution x^* of the sparse problem is always a solution of the cardinality constrained problem with $\kappa := ||x^*||_0$.

Relation to Sparse Optimization Problems



For some weight $\rho > 0$ consider

$$\min_{x} f(x) + \rho ||x||_{0}$$
 s.t. $g(x) \le 0$, $h(x) = 0$.

- ▶ Sparse → Cardinality: A solution x^* of the sparse problem is always a solution of the cardinality constrained problem with $\kappa := ||x^*||_0$.
- ► Cardinality → Sparse: Consider the following example by O. Burdakov

$$f(x) = ||Ax - b||_2^2$$
, where $A = \begin{pmatrix} 0 & 3 & -3 \\ 3 & 2 & 2 \\ 3 & 3 & 3 \end{pmatrix}$ and $b = \begin{pmatrix} 0 \\ 0 \\ 6 \end{pmatrix}$.

There is no $\rho \geq 0$ for which one obtains the same solution as for $\kappa = 2$.

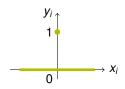


Continuous Reformulation using Complementarity Constraints



Idea: Introduce binary variables y counting the zeros of x:

$$x \circ y = 0$$
, $||x||_0 \le n - e^T y \le \kappa$.



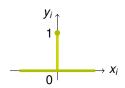
Continuous Reformulation using Complementarity Constraints



Idea: Introduce binary variables y counting the zeros of x:

$$x \circ y = 0$$
, $||x||_0 \le n - e^T y \le \kappa$.

Relax the binary variables to $y \in [0, e]$.



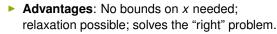
Continuous Reformulation using Complementarity Constraints



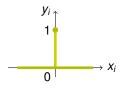
Idea: Introduce binary variables y counting the zeros of x:

$$x \circ y = 0$$
, $||x||_0 \le n - e^T y \le \kappa$.

Relax the binary variables to $y \in [0, e]$.



Disadvantages: Introduces a complementarity-type condition.



Relation between the Original Problem and the Continuous Reformulation



Exercise

What is the relation between continuous reformulation

$$\min_{x,y} f(x) \quad s.t. \quad g(x) \le 0, \quad h(x) = 0,$$

$$0 \le y \le e, \quad e^{T} y \ge n - \kappa,$$

$$x \circ y = 0.$$

and the original problem

$$\min_{x} f(x)$$
 s.t. $g(x) \le 0$, $h(x) = 0$, $||x||_0 \le \kappa$?





Relation between the Original Problem and the Continuous Reformulation (continued)



Global Solutions:

 \triangleright x^* is a global solution of the original problem if and only if there exists y^* such that (x^*, y^*) is a global solution of the continuous reformulation.

Relation between the Original Problem and the Continuous Reformulation (continued)



Global Solutions:

 x^* is a global solution of the original problem if and only if there exists y^* such that (x^*, y^*) is a global solution of the continuous reformulation.

Local Solutions:

If x^* is a local solution of the original problem, then for every y such that (x^*, y) is feasible, it is a local solution of the continuous reformulation.





Relation between the Original Problem and the Continuous Reformulation (continued)



Global Solutions:

 x^* is a global solution of the original problem if and only if there exists y^* such that (x^*, y^*) is a global solution of the continuous reformulation.

Local Solutions:

- If x^* is a local solution of the original problem, then for every y such that (x^*, y) is feasible, it is a local solution of the continuous reformulation.
- If (x^*, y^*) is a local solution of the continuous reformulation and $||x^*||_0 = \kappa$, then x^* is a local solution of the original problem.

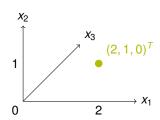


Example for Spurious Local Solutions



Consider the 3-dimensional cardinality constrained problem

$$\min_{x} \|x - (2, 1, 0)^{T}\|_{2}^{2} \quad \text{s.t.} \quad \|x\|_{0} \le 1.$$



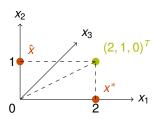
Example for Spurious Local Solutions



Consider the 3-dimensional cardinality constrained problem

$$\min_{x} \|x - (2, 1, 0)^{T}\|_{2}^{2} \quad \text{s.t.} \quad \|x\|_{0} \le 1.$$

The global minimizer is $x^* = (2, 0, 0)^T$ and the local minimizer $\hat{x} = (0, 1, 0)^T$.



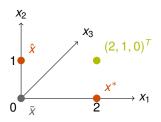
Example for Spurious Local Solutions



Consider the 3-dimensional cardinality constrained problem

$$\min_{x} \|x - (2, 1, 0)^{T}\|_{2}^{2} \quad \text{s.t.} \quad \|x\|_{0} \le 1.$$

The global minimizer is $x^* = (2, 0, 0)^T$ and the local minimizer $\hat{x} = (0, 1, 0)^T$.



However, the continuous relaxation has additional local minimizer such as (\tilde{x}, \tilde{y}) with $\tilde{x} = (0, 0, 0)^T$ and $\tilde{y} = (1, 1, 0)$.

Half and Full Complementarity Formulation

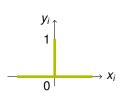


► The continuous reformulation results in

$$\min_{x,y} f(x) \quad \text{s.t.} \quad g(x) \le 0, \quad h(x) = 0,$$

$$0 \le y \le e, \quad e^{T} y \ge n - \kappa,$$

$$x \circ y = 0.$$



Half and Full Complementarity Formulation

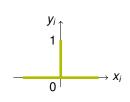


The continuous reformulation results in

$$\min_{x,y} f(x) \quad \text{s.t.} \quad g(x) \le 0, \quad h(x) = 0,$$

$$0 \le y \le e, \quad e^{T} y \ge n - \kappa,$$

$$x \circ y = 0.$$



► The full complementarity formulation is given by

$$\min_{x^{+}-x^{-},y} f(x^{+}-x^{-}) \quad \text{s.t.} \quad g(x^{+}-x^{-}) \leq 0, \quad h(x^{+}-x^{-}) = 0,$$

$$y \leq e, \quad e^{T}y \geq n - \kappa,$$

$$x^{+}, x^{-} \geq 0, \quad y \geq 0, \quad (x^{+}+x^{-}) \circ y = 0.$$



▶ In all points of interest MPCC-LICQ and MPCC-MFCQ are violated.





- In all points of interest MPCC-LICQ and MPCC-MFCQ are violated.
- ▶ MPCC theory generates conditions on the gradients with respect to *y* which are either violated or meaningless.



- In all points of interest MPCC-LICQ and MPCC-MFCQ are violated.
- ▶ MPCC theory generates conditions on the gradients with respect to *y* which are either violated or meaningless.
- ► The analogues of M-, C- and W-stationarity coincide.



- In all points of interest MPCC-LICQ and MPCC-MFCQ are violated.
- ▶ MPCC theory generates conditions on the gradients with respect to *y* which are either violated or meaningless.
- The analogues of M-, C- and W-stationarity coincide.
- All local minima of the continuous reformulation are S-stationary (= KKT points) under a Guignard-type CQ.





- In all points of interest MPCC-LICQ and MPCC-MFCQ are violated.
- ▶ MPCC theory generates conditions on the gradients with respect to *y* which are either violated or meaningless.
- The analogues of M-, C- and W-stationarity coincide.
- All local minima of the continuous reformulation are S-stationary (= KKT points) under a Guignard-type CQ.
- ► The Scholtes relaxation converges to S-stationary points under an MFCQ-type CQ.







Chance Constraints

Optimization Problems with Chance Constraints



An optimization problems with chance constraints is of the form

$$\min_{x} f(x) \quad \text{s.t.} \quad g(x) \le 0, \quad h(x) = 0,$$
$$P(G(x, \xi) \le 0) \ge \eta,$$

where

- u $\eta \in [0, 1]$ is the level of confidence, e.g. $\eta = 0.9, 0.95, 0.99$,
- \triangleright ξ is a random variable with finitely many possible realization $\xi_1 \dots, \xi_N$ and known probabilities p_1, \dots, p_N .

Example: Portfolio Optimization



Assume that

- we can invest in *n* assets.
- N possible scenarios *i* can occur with probabilities p_i and prognosed returns $\xi_i \in \mathbb{R}^n$,
- we want to invest a budget of 1 to maximize the expected return
- but limit the probability of having losses to $1 \eta \in (0, 1)$.

We have to solve

$$\max_{x} \sum_{i=1}^{N} p_{i} \xi_{i}^{T} x \quad \text{s.t.} \quad x \geq 0, \quad \sum_{i=1}^{n} x_{i} = 1,$$
$$P(\xi^{T} x \geq 0) \geq \eta$$

Reformulation of Chance Constraints



The chance constrained problem

$$\min_{x} f(x) \quad \text{s.t.} \quad g(x) \leq 0, \quad h(x) = 0, \quad P(G(x, \xi) \leq 0) \geq \eta,$$

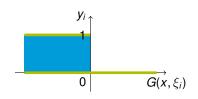
can equivalently be rewritten as

$$\min_{x,y} f(x) \quad \text{s.t.} \quad g(x) \le 0, \quad h(x) = 0,$$

$$y \in \{0,1\}^N,$$

$$p^T y \ge \eta,$$

$$y_i G(x, \xi_i) < 0.$$



Similarly to cardinality constraints, we can relax the binary variables to $y \in [0, 1]^N$.

What should you remember?



- There are many classes of optimization problems with similar structures/problems as MPCCs.
- Reformulating them as an MPCC is not always the best approach.
- But one can use ideas from MPCCs to handle these classes such as
 - decomposition of the feasible set into easier pieces,
 - nonsmooth reformulation,
 - using normal cones to obtain conditions on multipliers.



What did we do this week?



