



Solving MPEC Models with the KNITRO Nonlinear Solver

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Outline

1. KNITRO Short Introduction
2. What Are MPECs and Why Are They Useful?
3. Application in OPF Models (faster alternative to MIP)

The KNITRO solver (in a nutshell)

KNITRO: short introduction

KNITRO is a *commercially supported* optimization toolbox with a focus on solving large-scale **nonlinear optimization** problems.

Developed by **Ziena** Optimization LLC since 2001, distributed/supported by **Artelys**

Key features

- Active-set and interior-point/barrier algorithms for continuous optimization
- MINLP algorithms and **complementarity constraints** for discrete optimization
- Parallel multi-start heuristic for global optimization of non-convex problems
- Other notable features:
 - presolver, crossover, run all algorithms in parallel, derivative approximations, fast infeasibility detection
 - **tuner** (coming soon in 9.0)

Supported interfaces

- C/C++, Java, Fortran, Python
- **AMPL**, AIMMS, GAMS
- MATLAB

Supported platforms: Windows 32-bit, 64-bit, Linux 64-bit, Mac OS X 64-bit

Widely used in academia and industry

Mathematical Programs with Equilibrium Constraints (MPEC)

Mathematical Program w/ Equilibrium Constraint (MPEC)

Math Programming with Equilibrium Constraints
aka: Complementarity Constraints (MPCC)

$$\begin{aligned} \min & f(x) \\ \text{s.t.} & g(x) \geq 0 \\ & h(x) = 0 \end{aligned}$$

$$0 \leq x_1 \perp x_2 \geq 0$$

Applications:

- Strategic bidding
- Economic models
- Contact problems
- Traffic equilibrium
- Disjunctive conditions

The complementarity condition means

$$\begin{aligned} & x_1 \geq 0, x_2 \geq 0 \quad \text{and} \\ & \text{either } x_1 = 0 \quad \text{or } x_2 = 0 \quad (\text{equivalently, } x_1 x_2 = 0) \end{aligned}$$

Why is MPEC Hard?

$$\min f(x)$$

$$\text{s.t. } g(x) \geq 0$$

$$h(x) = 0$$

$$0 \leq x_1 \perp x_2 \geq 0$$



- Optimality conditions for NLP **assume** constraints satisfy some nice conditions (*constraint qualification*); *Constraint qualifications do not hold for MPECs*
- No interior path for interior-point methods
- Inconsistent constraint linearizations for SQP methods
- Unbounded multipliers

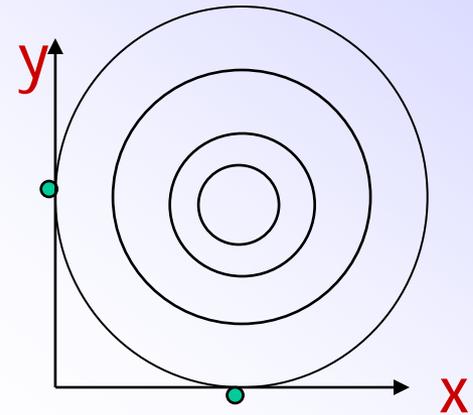
Why is MPEC Hard ? (example)

$$\min (x-1)^2 + (y-1)^2$$

$$c_1 = x \geq 0, \quad c_2 = y \geq 0$$

$$c_3 = xy = 0$$

$$\nabla c_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \quad \nabla c_3 = \begin{pmatrix} y \\ x \end{pmatrix}$$



$$\text{When } x=0, \quad \nabla c_3 = \alpha \nabla c_1$$

Linear dependent constraint gradients at every feasible point!

Why is MPEC Hard (in practice)?

What does this mean in practice?

- Numerical difficulties for the solver (e.g. singular linear systems)
- Challenges identifying solutions (finding multipliers to satisfy KKT conditions)

How to deal with it in practice?

- Need to identify and apply special treatment to these constraints
- *Relax, regularize or penalize* them in some way

Recent research breakthroughs allow reformulation for interior-point solvers via **penalization**

$$\begin{array}{ccc} \min f(x) & & \min f(x) + \pi x_1^T x_2 \\ \text{s.t. } g(x) \geq 0 & \longrightarrow & \text{s.t. } g(x) \geq 0 \\ h(x) = 0 & & h(x) = 0 \\ \mathbf{0 \leq x_1 \perp x_2 \geq 0} & & x_1 \geq 0, x_2 \geq 0 \end{array}$$

KNITRO MPEC Benchmarks

Comparing CPU times on a sample of MPECs
Mittelmann Benchmarks (<http://plato.asu.edu/bench.html>)

problem	filter	LOQO	KNITRO
bem-milanc30-s	648	f	f
frictionalblock_5	f	f	1
frictionalblock_6	f	f	f
incid-set1-32	147	56	3
incid-set1c-32	100	50	1
incid-set2-32	165	42	2
incid-set2c-32	99	f	1
pack-comp1-32	150	f	1
pack-comp1c-32	15	f	1
pack-comp1p-32	234	f	1
pack-comp2-32	301	37	1
pack-comp2p-32	186	f	1
pack-rig1-32	71	f	f
pack-rig1c-32	14	f	1

problem	filter	LOQO	KNITRO
pack-rig1p-32	64	29	1
pack-rig2-32	f	f	f
pack-rig2c-32	f	f	479
pack-rig2p-32	39	f	1
pack-rig3-32	65	f	1
pack-rig3c-32	15	f	1
siouxfls1	90	f	f
siouxfls	213	f	f

Binary variables vs MPECs

Binary variable: $x=0$ or $x=1$ (disjunction)

NLP/MPEC form:

Let $y=x-1$ and represent as $\mathbf{0} \leq x \perp y \geq \mathbf{0}$

Comparison:

- MIP vs. NLP/MPEC
- MIP gives global solution (but may be too hard to solve)
- NLP/MPEC form creates lots of non-convexity
 - Can create many local solutions (and locally infeasible points!)
 - ...but can solve quickly (use as heuristic for MIP)

THE OPF PROBLEM

4 AC-OPF model

- | Polar PQV formulation
- | Limits on voltage magnitudes
- | Maximum intensity levels on lines (nonlinear inequality constraints)
- | Limits on production levels
- | Kirchhoff law at each node (nonlinear equality constraints)

4 Generators operational constraints

- | The active (P) and reactive (Q) power of a production group are
 - bounded if the group is ON
 - zeros if the group is OFF

4 Objective

- | **Minimize losses** → similar to minimizing total production

MINLP APPROACH

▣ Group is OFF

$$P = 0$$

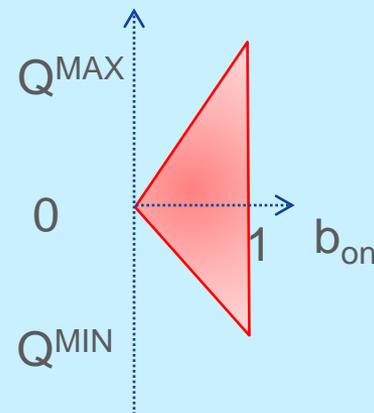
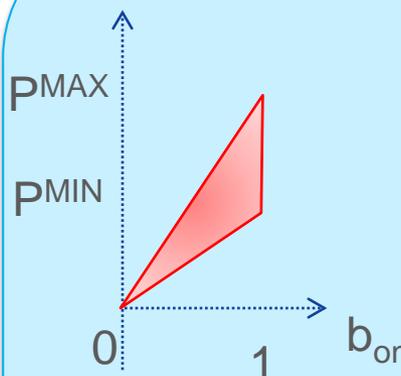
$$Q = 0$$

▣ Group is ON

$$P \in [P^{MIN}, P^{MAX}]$$

$$Q \in [Q^{MIN}, Q^{MAX}]$$

MINLP



$$b_{on} \in \{0,1\}$$

$$P^{MIN} \cdot b_{on} \leq P \leq P^{MAX} \cdot b_{on}$$

$$Q^{MIN} \cdot b_{on} \leq Q \leq Q^{MAX} \cdot b_{on}$$

4 Use of an instance from the literature (IEEE)

- | Network composed of 662 nodes
- | Input data : topology, productions and consumptions, limits on power and voltage
- | Some phase-shifting transformers have variable transformer ratio

4 Generation of 100 problem instances

- | Modifying production groups by adding a minimum capacity limit
 - Minimum capacity set to half of the maximum capacity
- | Perturbation of consumption ($\pm 50\%$)
 - Conservation of the total demand in active/reactive power

Algorithm : Branch-and-Bound of KNITRO 8.1.1

| Intel Core 2 Duo @ 2.80 Ghz 4Go RAM

Average 13.2 seconds by instance

100 % success rate

Can we do faster ?

MPEC FORMULATIONS

▣ Use of complementarity constraints (MPEC)

| $0 \leq x \perp y \geq 0 \Leftrightarrow (x = 0 \text{ or } y = 0) \text{ and } (x, y \geq 0)$

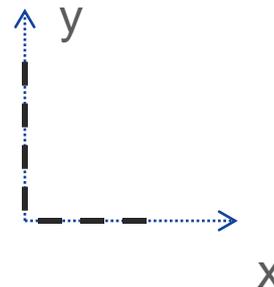
| Non-convex constraints on continuous variables

▣ Various mathematical formulations are possible:

| $0 \leq x, y \quad xy \leq \varepsilon$

| $0 \leq x, y$ and addition of a penalty term $\pi \cdot x \cdot y$

▣ Geometric representation:

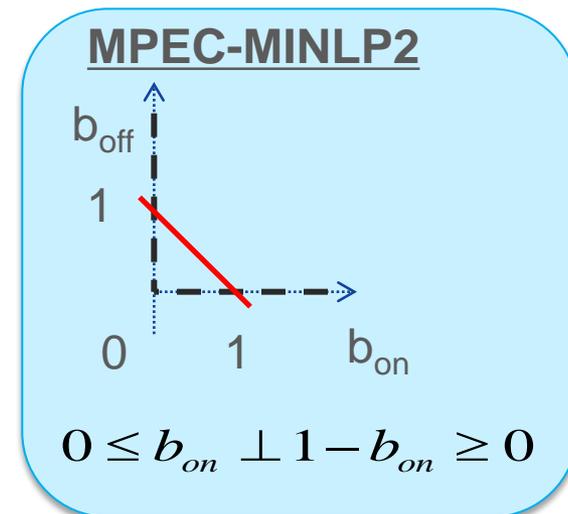
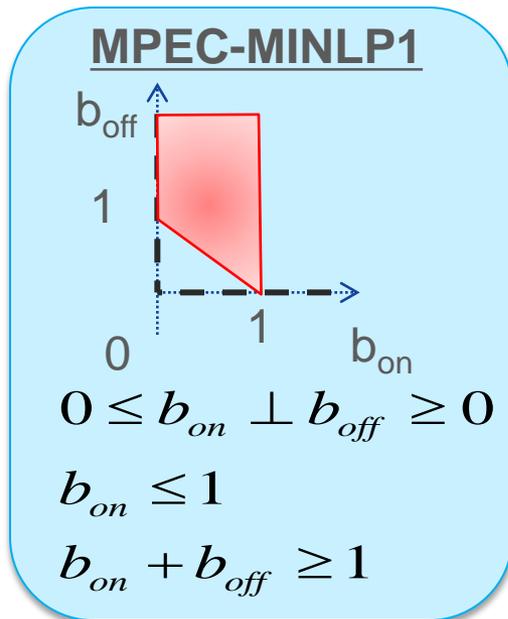


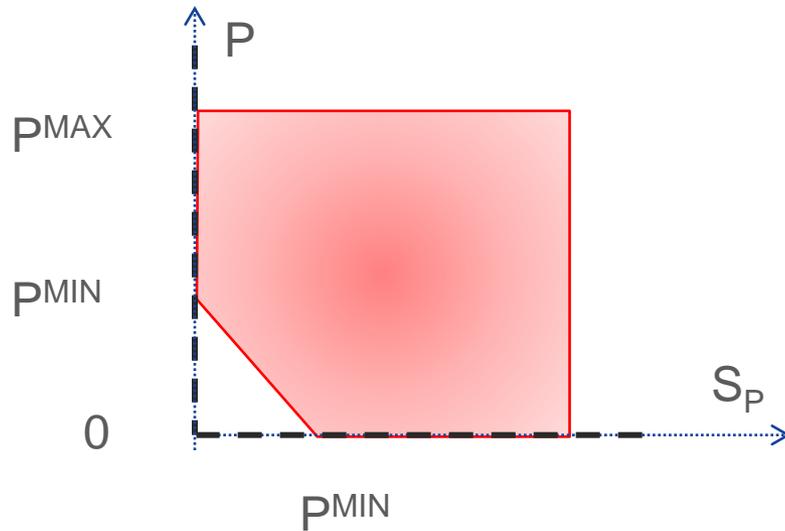
4 Reformulation of $b_{on} \in \{0,1\}$ as an intersection of

| linear polyhedron: $P^{MIN} \cdot b_{on} \leq P \leq P^{MAX} \cdot b_{on}$

$$Q^{MIN} \cdot b_{on} \leq Q \leq Q^{MAX} \cdot b_{on}$$

| complementarity constraints





▣ Reformulation of constraints on active/reactive powers P and Q instead of b_{on}

| Leads to MPEC constraints linking P , Q and a new continuous slack variable S_p

MPEC-NLP1

$$0 \leq P + Q^2 \perp S_P \geq 0$$

$$P + S_P \geq P^{MIN}$$

$$0 \leq P \leq P^{MAX}$$

$$Q^{MIN} \leq Q \leq Q^{MAX}$$

MPEC-NLP2

$$0 \leq P + Q^+ + Q^- \perp S_P \geq 0$$

$$Q = Q^+ - Q^-, Q^+ \geq 0, Q^- \geq 0$$

$$P + S_P \geq P^{MIN}$$

$$0 \leq P \leq P^{MAX}$$

$$Q^{MIN} \leq Q \leq Q^{MAX}$$

COMPUTATIONAL EXPERIMENTS

Average results on the 100 instances
 With KNITRO 8.1.1 on Intel Core 2 Duo @ 2.80 Ghz 4Go RAM

Formulation	CPU time (s)	Losses (SU)	% ON	% SUCCESS
MINLP	13.2	3.12	98.6	100
MPEC-MINLP1	1.89	5.08	80.6	80
MPEC-MINLP2	0.85	3.80	94.4	98
MPEC-NLP1	1.33	3.16	99.7	98
MPEC-NLP2	2.03	4.01	91.8	100

- ⚡ The MPEC heuristics are faster than the MINLP approaches
- ⚡ The various approaches converge to different solution points
 - | with varying numbers of active generators
 - | with varying losses

Average results on the 100 instances
 With KNITRO 8.1.1 on Intel Core 2 Duo @ 2.80 Ghz 4Go RAM

Formulation	CPU time (s)	Losses (SU)	% ON	% SUCCESS
MINLP	13.2	3.12	98.6	100
MPEC-MINLP2	0.85	3.80	94.4	98
MPEC-NLP1	1.33	3.16	99.7	98

- ▣ MPEC-NLP1 converge towards solutions close to MINLP
 - | in terms of losses (near-optimal solutions)
 - | in terms of active production groups

- ▣ MPEC-MINLP2 is faster than MPEC-NLP1
 - | but losses are higher (sub-optimal solutions)

- ▣ MPEC models may be a good heuristics alternative to solve non-convex MINLP problems
 - | Branch-and-bound tends to be slow
 - | Good when combinatorial choices are not too hard
- ▣ Some success in applying this technique to AC-OPD models
 - | Use complementarity constraints to model startup/shutdown decisions
- ▣ Future work (iTesla project)
 - | Apply to large instances
 - >7000 nodes, >8000 lines
 - | Analyze robustness on a large number of instances

THANK YOU FOR YOUR ATTENTION

TRIAL VERSION CAN BE DOWNLOADED AT

[HTTP://WWW.ZIENA.COM/TRIAL.HTML](http://www.ziena.com/trial.html)

MORE INFO AT

[HTTP://WWW.ARTELYS.COM/KNITRO](http://www.artelys.com/knitro)

▣ Trial version can be downloaded at

▣ <http://www.ziena.com/trial.html>

▣ More info at

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