

The moment hierarchy in polynomial optimization: introduction and application to power systems

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What is polynomial optimization ?

$$\rho = \min_{x \in \mathcal{X}} f(x) \quad (\text{POP})$$

- $\mathcal{X} = \{x \in \mathbb{R}^n \mid g_j(x) \geq 0, \forall j \in \llbracket 1, m \rrbracket\}$
- f and all g_j are polynomial functions
- we assume that (POP) has a solution (e.g. \mathcal{X} is nonempty and compact)

Example (a nonconvex QCQP)

$$\begin{aligned} \rho &= \min_{x \in \mathbb{R}^2} x_1 \\ \text{s.t.} \quad & 2x_1 - x_2 + 1 \geq 0 \\ & 2x_1 + x_2 + 1 \geq 0 \\ & x_1^2 + x_2^2 = 1 \end{aligned}$$

All the world is a POP! (...almost)

Example (a MILP — minimum vertex cover)

$$\begin{aligned} \rho &= \min_{x \in \mathbb{R}^{|V|}} \sum_{v \in V} x_v \\ \text{s.t. } & x_u + x_v \geq 1, \quad \forall (u, v) \in E \\ & x_v \in \{0, 1\}, \quad \forall v \in V \quad \rightarrow \quad x_v = x_v^2 \end{aligned}$$

Example (an exotic POP)

$$\begin{aligned} \rho &= \min_{x \in \mathbb{R}^2} x_1 x_2 - x_1^3 \\ \text{s.t. } & 5 - x_1^4 - 2x_2^2 \geq 0 \\ & 2x_1^2 + x_2 + 1 = 0 \end{aligned}$$

Outline of the presentation

1. The moment-SOS hierarchy for polynomial optimization
2. The AC-OPF problem: POP formulation and scalability issues
3. Conclusion and perspectives

1. The moment-SOS hierarchy for polynomial optimization

Background notions

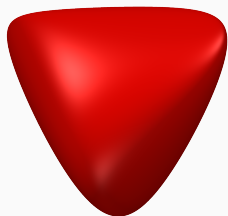
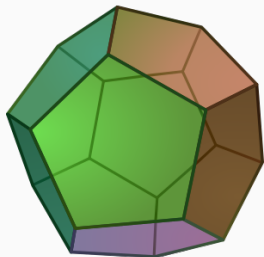
The moment hierarchy

The sum-of-squares hierarchy

Some important results

Linear vs semidefinite programming

$$\min_{x \in \mathbb{R}^n} \langle x, c \rangle \quad \text{s.t.} \quad \begin{cases} Ax = 0 \\ x \geq 0 \end{cases} \quad \text{vs} \quad \min_{X \in \mathcal{S}^n} \langle X, C \rangle \quad \text{s.t.} \quad \begin{cases} \mathcal{A}(X) = 0 \\ X \succeq 0 \end{cases}$$



(Images from Wikipedia)

Polynomials

For a polynomial $f \in \mathbb{R}[x_1, \dots, x_n]$ we write

$$f = \sum_{\alpha \in \mathbb{N}^n} f_{\alpha} x^{\alpha}$$

where

- $x^{\alpha} = x_1^{\alpha_1} x_2^{\alpha_2} \dots x_n^{\alpha_n}$ is the monomial labeled by $\alpha \in \mathbb{N}^n$
- $f_{\alpha} \in \mathbb{R}$ is the corresponding coefficient
- $\{x^{\alpha}\}_{\alpha \in \mathbb{N}^n}$ is the monomial basis of $\mathbb{R}[x_1, \dots, x_n]$
- for polynomials of degree at most k we truncate $\{x^{\alpha}\}_{\alpha \in \mathbb{N}^n}$ to labels in $\mathbb{N}_k^n = \{\alpha \in \mathbb{N}^n \mid \sum_{i=1}^n \alpha_i \leq k\}$

Quadratic module

- The polynomial $f \in \mathbb{R}[x_1, \dots, x_n]$ is SOS if $f = \sum_{i \in \llbracket 1, p \rrbracket} f_i^2$ for some polynomials $f_i \in \mathbb{R}[x_1, \dots, x_n]$
- The quadratic module of \mathcal{X} is the set

$$\mathcal{Q}(\mathcal{X}) = \left\{ \sigma_0 + \sum_{j \in \llbracket 1, m \rrbracket} \sigma_j g_j \mid \{\sigma_j\}_{j \in \llbracket 0, m \rrbracket} \text{ are SOS polynomials} \right\}$$

- $\mathcal{Q}(\mathcal{X})$ is said to be Archimedean if for some $M > 0$
 $M - \sum_{i \in \llbracket 1, n \rrbracket} x_i^2 \in \mathcal{Q}(\mathcal{X})$

NB: $\mathcal{Q}(\mathcal{X} \cap \mathbb{B}_r)$ is Archimedean for any $r > 0$

1. The moment-SOS hierarchy for polynomial optimization

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Some important results

POP as a moment problem

$$\begin{aligned}\rho = \min_{x \in \mathcal{X}} f(x) &= \inf_{\mu \in \mathcal{M}(\mathcal{X})} \int_{\mathbb{R}^n} f(x) \mu(dx) \\ &= \inf_{\mu \in \mathcal{M}(\mathcal{X})} \sum_{\alpha \in \mathbb{N}^n} f_\alpha \int_{\mathbb{R}^n} x^\alpha \mu(dx) \\ &= \inf \left\{ \sum_{\alpha \in \mathbb{N}^n} f_\alpha y_\alpha \mid \text{"}y \text{ has a representing measure on } \mathcal{X} \text{"} \right\}\end{aligned}$$

Proposition (necessary condition)

If $y \in \mathbb{R}^{\mathbb{N}_{2d}^n}$ is the sequence of moments (up to order $2d$) of a measure supported by the set $\mathcal{X} = \{x \in \mathbb{R}^n \mid g_j(x) \geq 0, \forall j \in \llbracket 1, m \rrbracket\}$, then

- $M_d(y) \succeq 0$ (moment matrix)
- $M_{d-d_j}(g_j y) \succeq 0, \forall j \in \llbracket 1, m \rrbracket$ (localizing matrices)

Moment matrices ?

$$M_d(y) = (y_{\alpha+\beta})_{\alpha \in \mathbb{N}_d^n, \beta \in \mathbb{N}_d^n}$$

$$M_{d-d_j}(g_j y) = \left(\sum_{\gamma \in \text{supp}(g_j)} g_{j,\gamma} y_{\alpha+\beta+\gamma} \right)_{\alpha \in \mathbb{N}_{d-d_j}^n, \beta \in \mathbb{N}_{d-d_j}^n} \quad \left(d_j = \left\lceil \frac{\deg(g_j)}{2} \right\rceil \right)$$

Example

For $n = 2$ and $d = 1$, $M_d(y) \succeq 0$ writes as

$$\begin{pmatrix} y_{00} & y_{10} & y_{01} \\ y_{10} & y_{20} & y_{11} \\ y_{01} & y_{11} & y_{02} \end{pmatrix} \succeq 0$$

NB: we need $d \geq \underline{d} = \max \left(\{d_j\}_{j \in \llbracket 1, m \rrbracket}, \left\lceil \frac{\deg(f)}{2} \right\rceil \right)$ for (POP)

The truncated moment hierarchy

$$\begin{aligned} \rho_d^{\text{MOM}} &= \inf_{y \in \mathbb{R}^{|N_{2d}^n|}} \sum_{\alpha \in N_{2d}^n} f_\alpha y_\alpha && (\text{MOM}_d) \\ \text{s.t.} \quad & M_d(y) \succeq 0 \\ & M_{d-d_j}(g_j y) \succeq 0, \quad \forall j \in \llbracket 1, m \rrbracket \\ & y_{(0, \dots, 0)} = 1 \end{aligned}$$

Theorem (Lasserre [2001])

If the set \mathcal{X} is compact and the quadratic module $\mathcal{Q}(\mathcal{X})$ is Archimedean, then the monotonous non-decreasing sequence of values $\{\rho_d^{\text{MOM}}\}_{d \geq d}$ of (MOM_d) converges to the value ρ of (POP) .

Example (nonconvex QCQP continued)

$$\begin{aligned} \rho_1^{\text{MOM}} &= \min_{y \in \mathbb{R}^6} y_{10} \\ \text{s.t.} \quad & \begin{pmatrix} y_{00} & y_{10} & y_{01} \\ y_{10} & y_{20} & y_{11} \\ y_{01} & y_{11} & y_{02} \end{pmatrix} \succeq 0 \\ & 2y_{10} - y_{01} + 1 \geq 0 \\ & 2y_{10} + y_{01} + 1 \geq 0 \\ & y_{20} + y_{02} - 1 = 0 \\ & y_{00} = 1 \end{aligned}$$

1. The moment-SOS hierarchy for polynomial optimization

Background notions

The moment hierarchy

The sum-of-squares hierarchy

Some important results

$$\rho = \min_{x \in \mathcal{X}} f(x) = \sup_{\gamma \in \mathbb{R}} \gamma, \quad \text{s.t. } f(x) - \gamma \geq 0, \quad \forall x \in \mathcal{X}$$

$$\geq \sup_{\gamma \in \mathbb{R}} \gamma, \quad \text{s.t. } f - \gamma \in \mathcal{Q}(\mathcal{X})$$

Proposition (Putinar's Positivstellensatz)

If the quadratic module $\mathcal{Q}(\mathcal{X})$ is Archimedean, then $f - \gamma > 0$ on \mathcal{X} implies that $f - \gamma \in \mathcal{Q}(\mathcal{X})$.

The truncated sum-of-squares hierarchy

$$\begin{aligned} \rho_d^{\text{SOS}} = \sup_{\substack{\gamma \in \mathbb{R} \\ Z_j \in \mathcal{S}^{\lfloor \frac{n}{2} - d_j \rfloor}}} \gamma & \quad (\text{SOS}_d) \\ \text{s.t.} \quad f_0 - \gamma &= \sum_{j \in \llbracket 0, m \rrbracket} \langle A_{j,0}, Z_j \rangle \\ f_\alpha &= \sum_{j \in \llbracket 0, m \rrbracket} \langle A_{j,\alpha}, Z_j \rangle, \quad \forall \alpha \in \mathbb{N}_{2d}^n \setminus \{0\} \\ Z_j &\succeq 0, \quad \forall j \in \llbracket 1, m \rrbracket \end{aligned}$$

Proposition (Josz and Henrion [2016])

In general $\rho_d^{\text{SOS}} \leq \rho_d^{\text{MOM}}$ (weak duality). If Moreover, the set \mathcal{X} is Archimedean, then $\rho_d^{\text{SOS}} = \rho_d^{\text{MOM}}$.

Sum-of-squares polynomials ?

σ_j of degree $2d$ is SOS

iff $\sigma_j(x) = \left\langle Z_j, (x^{\alpha+\beta})_{\alpha \in \mathbb{N}_d^n, \beta \in \mathbb{N}_d^n} \right\rangle$ for some $Z_j \succeq 0$

Example

For $n = 2$ and $d = 1$, σ_0 is SOS writes as

$$\sigma_0(x) = \left\langle Z_0, \begin{pmatrix} 1 & x_1 & x_2 \\ x_1 & x_1^2 & x_1 x_2 \\ x_2 & x_1 x_2 & x_2^2 \end{pmatrix} \right\rangle \text{ for some } Z_0 \succeq 0$$

SOS relaxations are semidefinite programs

Example (nonconvex QCQP continued)

$$\begin{aligned} \rho_1^{\text{SOS}} = & \max_{\substack{(\gamma, z_1, z_2, z_3) \in \mathbb{R}^4 \\ Z_0 \in \mathcal{S}^3}} \gamma \\ \text{s.t.} \quad & -\gamma = Z_0^{1,1} + z_1 + z_2 - z_3 \\ & 1 = (Z_0^{1,2} + Z_0^{2,1}) + 2z_1 + 2z_2 \\ & 0 = (Z_0^{1,3} + Z_0^{3,1}) - z_1 + z_2 \\ & 0 = (Z_0^{2,3} + Z_0^{3,2}) \\ & 0 = Z_0^{2,2} + z_3 \\ & 0 = Z_0^{3,3} + z_3 \\ & z_1 \geq 0, \quad z_2 \geq 0, \quad z_3 \geq 0 \\ & Z_0 \succeq 0 \end{aligned}$$

1. The moment-SOS hierarchy for polynomial optimization

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Some important results

Finite convergence

Theorem (Nie [2014])

Suppose that the quadratic module $Q(\mathcal{X})$ is Archimedean.

If the constraint qualification, strict complementarity and second order sufficiency conditions hold at every global minimizer of (POP), then the sequence $\{\rho_d^{\text{MOM}}\}_{d \geq \underline{d}}$ converges in finitely many steps.

Example (nonconvex QCQP continued)

bound	ρ_1^{MOM}	ρ_2^{MOM}	$\bar{\rho}$ (NLP)
value	-0.50	0.00	0.00

NB: finite convergence holds “generically”

Extracting a solution

Theorem (Curto and Fialkow [2000], Henrion and Lasserre [2005])

At step $d \geq \underline{d}$ of the moment hierarchy, if an optimal solution y^* of (MOM_d) satisfies $\text{rank}(M_{d-\underline{d}}(y^*)) = \text{rank}(M_d(y^*))$ then $\rho_d^{MOM} = \rho$ and (POP) has at least $\text{rank}(M_d(y^*))$ solutions that can be extracted by a linear algebra routine.

Example (nonconvex QCQP continued)

At step $d = 2$, we obtain a solution y^* satisfying

$$\text{spec}(M_1(y^*)) \simeq \begin{pmatrix} 1.00 \\ 0.99 \\ 0.00 \end{pmatrix} \quad \text{and} \quad \text{spec}(M_2(y^*)) \simeq \begin{pmatrix} 1.99 \\ 0.99 \\ 0.00 \\ 0.00 \\ 0.00 \\ 0.00 \end{pmatrix}$$

and (POP) has exactly $d = 2$ solutions $(0, 1)$ and $(0, -1)$

Key takeaway

Convergence of the Moment-SOS hierarchy of semidefinite programs

$$\rho = \min_{x \in \mathcal{X}} f(x)$$

$$\begin{array}{ccc} \nearrow & & \nwarrow \\ \vdots & & \vdots \\ \rho_{d+1}^{\text{MOM}} & \geq & \rho_{d+1}^{\text{SOS}} \\ \geq & & \geq \\ \rho_d^{\text{MOM}} & \geq & \rho_d^{\text{SOS}} \end{array}$$

$$d \geq \max \left(\{d_j\}_{j \in \llbracket 1, m \rrbracket}, \left\lceil \frac{\deg(f)}{2} \right\rceil \right)$$

2. The AC-OPF problem: POP formulation and scalability issues

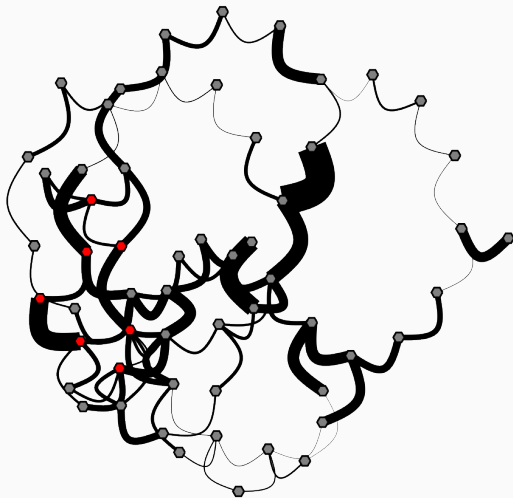
The alternative current - optimal power flow problem

Scalability issues

Sparsity

First order methods

PGLib's case 57 IEEE



Notations for the AC-OPF problem

$$\min_{\substack{v \in \mathbb{C}^{|\mathcal{N}|} \\ s \in \mathbb{C}^{|\mathcal{G}|} \\ s^\ell \in \mathbb{C}^{2|\mathcal{E}|}}} \sum_{g \in \mathcal{G}} C_{2,g} \Re(s_g)^2 + C_{1,g} \Re(s_g) + C_{0,g} \quad (\text{AC-OPF})$$

$$\text{s.t.} \quad \angle v_i = 0, \quad \forall i \in \mathcal{N}_r$$

$$\underline{S}_g \leq s_g \leq \overline{S}_g, \quad \forall g \in \mathcal{G}$$

$$\underline{V}_i \leq |v_i| \leq \overline{V}_i, \quad \forall i \in \mathcal{N}$$

$$\sum_{g \in \mathcal{G}(i)} s_g - L_i - (Y_i^s)^* |v_i|^2 = \sum_{j \in \mathcal{N}(i)} s_{i,j}^\ell, \quad \forall i \in \mathcal{N}$$

$$s_{i,j}^\ell = (Y_{i,j} + Y_{i,j}^c)^* \frac{|v_i|^2}{|T_{i,j}|^2} - Y_{i,j}^* \frac{v_i v_j^*}{T_{i,j}}, \quad \forall (i,j) \in \mathcal{E}$$

$$s_{j,i}^\ell = (Y_{i,j} + Y_{j,i}^c)^* |v_j|^2 - Y_{i,j}^* \frac{v_i^* v_j}{T_{i,j}^*}, \quad \forall (i,j) \in \mathcal{E}$$

$$|s_{i,j}^\ell| \leq \overline{S}_{i,j}, \quad \forall j \in \mathcal{N}(i), \quad \forall i \in \mathcal{N}$$

$$\underline{\Theta}_{i,j} \leq \angle v_i v_j^* \leq \overline{\Theta}_{i,j}, \quad \forall (i,j) \in \mathcal{E}$$

Polynomial optimization for AC-OPF

$$v_i = a_i + \mathbf{i}b_i, \quad \forall i \in \llbracket 1, n \rrbracket$$

Example (complex line power)

$$s_{i,j}^{\ell} = Z_{i,j}|v_i|^2 + Z'_{i,j}v_iv_j^*$$

$$\iff$$

$$\begin{cases} \Re(s_{i,j}^{\ell}) = \Re(Z_{i,j})(a_i^2 + b_i^2) + \Re(Z'_{i,j})(a_ia_j + b_ib_j) - \Im(Z'_{i,j})(a_jb_i - a_ib_j) \\ \Im(s_{i,j}^{\ell}) = \Im(Z_{i,j})(a_i^2 + b_i^2) + \Im(Z'_{i,j})(a_ia_j + b_ib_j) + \Re(Z'_{i,j})(a_jb_i - a_ib_j) \end{cases}$$

The AC-OPF problem can be written in form (POP)!

2. The AC-OPF problem: POP formulation and scalability issues

The alternative current - optimal power flow problem

Scalability issues

Sparsity

First order methods

Scalability issues

- AC-OPF IEEE case 57 (no line/angle limits) \rightarrow POP

	(POP)
variables	128
eq. constraints	115
ineq. constraints	128

- POP \rightarrow moment relaxation

	$d = 1$	$d = 2$
size(y)	8.385	12.082.785

ρ_2^{MOM} for PGLib's case 57 IEEE is intractable!
(with current computers and SDP solvers)

AC-OPF instances formulate as POPs but...
typical problems at RTE have over 6000 nodes!

what do we do ?

...some ongoing research ideas

- Exploit the sparsity of (POP)
- Circumvent interior point (second order) SDP solvers
- Combining both ? HPC implementations ?

2. The AC-OPF problem: POP formulation and scalability issues

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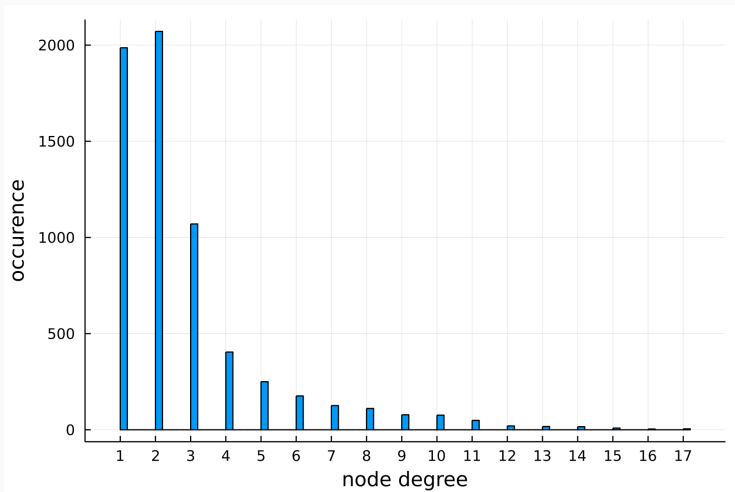
Scalability issues

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Sparsity structure in power grids

PGLib's case 6468 RTE



Exploiting correlative sparsity for POPs

$$\min_{x \in \mathbb{R}^3} x_1^2 + x_2^2 + x_3^2 + x_1x_2 + x_2x_3$$

Exploit absence of x_1x_3 product ? Set $\mathcal{I}_1 = \{1, 2\}$, $\mathcal{I}_2 = \{2, 3\}$

$$M_1(y) = \begin{pmatrix} y_{000} & y_{100} & y_{010} & y_{001} \\ y_{100} & y_{200} & y_{110} & y_{101} \\ y_{010} & y_{110} & y_{020} & y_{011} \\ y_{001} & y_{101} & y_{011} & y_{002} \end{pmatrix} \succeq 0 \quad \text{vs} \quad \begin{cases} M_1(y|\mathcal{I}_1) \succeq 0 \\ M_1(y|\mathcal{I}_2) \succeq 0 \end{cases}$$

Reduce moment variables (MOM_d) / matrices size (SOS_d)

A sparse moment hierarchy

$$\begin{aligned} \rho_d^{\text{CS-MOM}} &= \inf_{y \in \mathbb{R}^{n(\mathcal{I})}} \sum_{\alpha \in \text{supp}(f)} f_\alpha y_\alpha && (\text{CS-MOM}_d) \\ \text{s.t.} \quad & M_d(y|\mathcal{I}_k) \succeq 0, \quad \forall k \in \llbracket 1, p \rrbracket \\ & M_{d-d_j}(g_j y|\mathcal{I}_k) \succeq 0, \quad \forall j \in \llbracket 1, m \rrbracket, \quad \forall k \in \llbracket 1, p \rrbracket \\ & y_{(0, \dots, 0)} = 1 \end{aligned}$$

Theorem (Lasserre [2006])

Suppose that the set \mathcal{X} is compact and the quadratic module $\mathcal{Q}(\mathcal{X})$ is Archimedean. If the variable set $\mathcal{I} = \{\mathcal{I}_k\}_{k \in \llbracket 1, p \rrbracket}$ satisfies the running intersection property (RIP), then the monotonous non-decreasing sequence of values $\{\rho_d^{\text{CS-MOM}}\}_{d \geq \underline{d}}$ of (CS-MOM_d) converges to the value ρ of (POP).

NB: the maximum cliques of a chordal graph satisfy the RIP

IEEE case 57 after chordal extension + cliques: $\begin{cases} |\mathcal{I}| = 52 \\ \max_{k \in \llbracket 1, p \rrbracket} |\mathcal{I}_k| = 26 \end{cases}$

- POP \rightarrow sparse moment relaxation

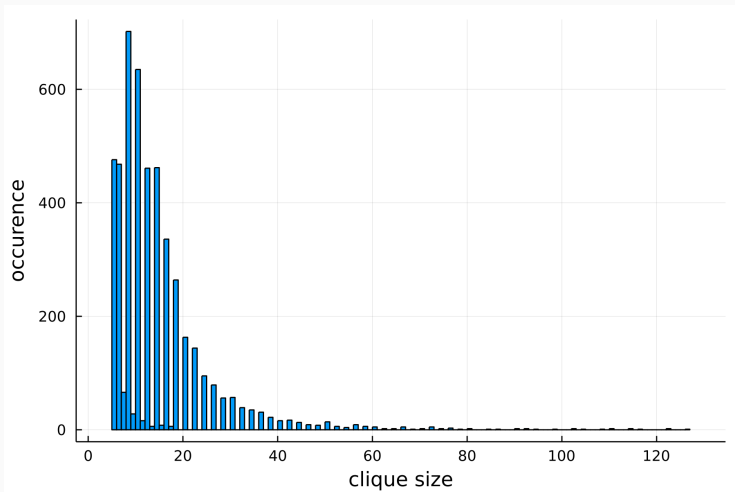
	$d = 1$	$d = 2$
size(y)	1.950	122.286

- numerical result (IEEE case 57 perturbed):

	value	gap to $\bar{\rho}$ (%)	time (s)
$\bar{\rho}$	2433.89	-	4.18
$\rho_2^{\text{CS-MOM}}$	2433.89	0.00	8356.59
$\rho_1^{\text{CS-MOM}}$	2359.58	3.05	0.75

Rip the RIP ?

PGLib's case 6468 RTE



Replace the RIP with grid clustering

PGLib's case 57 IEEE perturbed

instances	value (k\$/h)			time (s)	
	$\rho_1(\mathcal{I}^{\text{RTE}})$	$\rho_2(\mathcal{I}^{\text{RTE}})$	$\bar{\rho}$	$\rho_1(\mathcal{I}^{\text{RTE}})$	$\rho_2(\mathcal{I}^{\text{RTE}})$
84	2357.95	2433.88	2433.88	0.58	6834.19
260	3481.80	3542.64	3542.64	0.79	5122.87
267	5265.35	5333.00	5333.00	0.92	6291.01
299	6144.88	6267.34	6267.34	0.63	7302.58
628	2316.76	2483.23	2483.23	0.59	5746.87
683	3129.71	3205.65	3205.64	0.62	6532.20
829	3523.47	3597.40	3597.39	0.50	5414.41
868	3977.68	4067.72	4067.72	0.72	6807.93
974	4446.70	4535.65	4535.64	0.58	6557.98

Further thoughts

- What convergence guarantees when the RIP does not hold ?
- Correlative sparsity can be advantageously combined with term sparsity [Wang et al., 2020]
- Correlative & term sparsity successfully certifies 1%-optimality for AC-OPF instances with up to 6515 nodes [Wang et al., 2022]
- Still challenging for many instances with +5000 nodes

2. The AC-OPF problem: POP formulation and scalability issues

The alternative current - optimal power flow problem

Scalability issues

Sparsity

First order methods

A dual decomposition method

New moment variables $y^k = \{y_\alpha \mid \text{supp}(\alpha) \subseteq \mathcal{I}_k\}$

$$\begin{aligned} \rho_d^{\text{CS-MOM}} &= \inf_{y \in \mathbb{Y}} \sum_{k \in \llbracket 1, p \rrbracket} \langle y^k, f^k \rangle \\ \text{s.t.} \quad & M_{d-d_j}(g_j y^k) \succeq 0, \quad \forall j \in \mathcal{J}_k^0, \quad \forall k \in \llbracket 1, p \rrbracket \\ & y_{(0, \dots, 0)}^k = 1, \quad \forall k \in \llbracket 1, p \rrbracket \\ & B_{k, k'}^k y^k + B_{k, k'}^{k'} y^{k'} = 0, \quad \forall (k, k') \in \mathcal{P} \end{aligned} \quad (*)$$

Next, we dualize the coupling constraints (*)

New dual problem

$$\theta_d^{\text{CS-MOM}} = \sup_{\lambda \in \Lambda} \Phi(\lambda)$$

where $\Phi = \sum_{k \in [1, p]} \phi^k$ and each ϕ^k is a (smaller) semidefinite program

$$\begin{aligned} \phi^k(\lambda) &= \inf_{y^k \in \mathbb{Y}^k} \langle y^k, f^k + A^k \lambda \rangle \\ \text{s.t.} \quad & M_{d-d_j}(g_j y^k) \succeq 0, \quad \forall j \in \mathcal{J}_k^0 \\ & y_{(0, \dots, 0)}^k = 1 \end{aligned}$$

When strong duality holds $\theta_d^{\text{CS-MOM}} = \rho_d^{\text{CS-MOM}}$

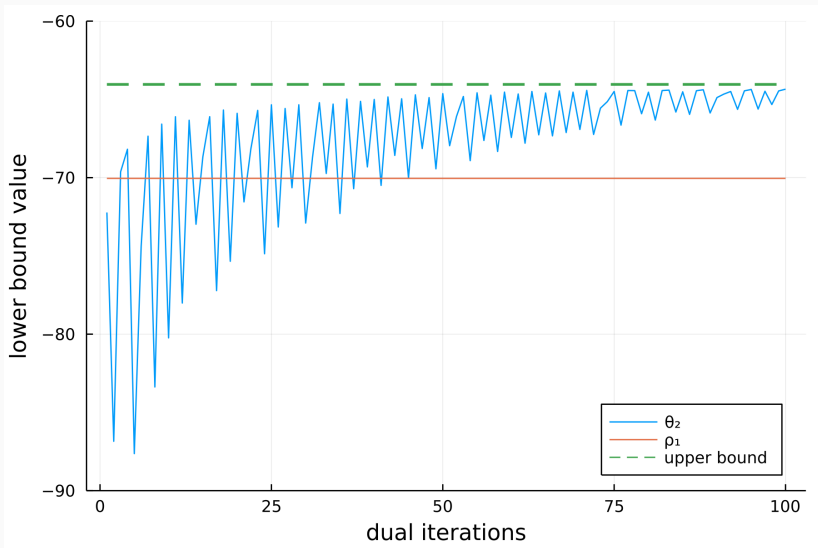
Numerical example (1/2)

A randomly generated QCQP with $n = 20$ variables

	value	gap to $\bar{\rho}$ (%)	time (s)
$\bar{\rho}$	-64.0435	—	3.129
$\theta_2^{\text{CS-MOM}}$	-64.3478	0.47	1258.811
$\rho_2^{\text{CS-MOM}}$	*	*	*
$\rho_1^{\text{CS-MOM}}$	-70.0464	9.37	0.02

- Computing $\rho_2^{\text{CS-MOM}}$ with Mosek and 8GB of RAM gives a memory error
- Computing $\theta_2^{\text{CS-MOM}}$ is less memory demanding (...but quite slow!)

Numerical example (2/2)



- Smoothing the dual problem ?
- Avoid solving SDP subproblems ?
- Approximate subproblems ? [Dathathri et al., 2020]
- Other first order SDP approaches [Yurtsever et al., 2021]

3. Conclusion and perspectives

Time to conclude !

Conclusion and perspectives

- POPs cover a large class of optimization problems
- The Moment-SOS hierarchy solves POPs via SDP relaxations
- Not covered in this talk: extensions to Control and PDE [Henrion et al., 2020], complex optimization [Josz and Molzahn, 2018], noncommutative optimization [Klep et al., 2022] etc. . .
- Large scale applications e.g. in AC-OPF are still challenging
- Combined use of sparsity and first order methods offer new perspectives

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