

LP formulations for mixed-integer polynomial optimization problems

Daniel Bienstock and Gonzalo Muñoz, Columbia University

An **application**: the Optimal Power Flow problem (ACOPF)

Input: an undirected graph G .

- For every vertex i , **two** variables: e_i and f_i
- For every edge $\{k, m\}$, **four** (specific) quadratics:

$$H_{k,m}^P(e_k, f_k, e_m, f_m), \quad H_{k,m}^Q(e_k, f_k, e_m, f_m)$$

$$H_{m,k}^P(e_k, f_k, e_m, f_m), \quad H_{m,k}^Q(e_k, f_k, e_m, f_m)$$



$$\min \sum_k F_k \left(\sum_{\{k,m\} \in \delta(k)} H_{k,m}^P(e_k, f_k, e_m, f_m) \right)$$

$$\text{s.t.} \quad L_k^P \leq \sum_{\{k,m\} \in \delta(k)} H_{k,m}^P(e_k, f_k, e_m, f_m) \leq U_k^P \quad \forall k$$

$$L_k^Q \leq \sum_{\{k,m\} \in \delta(k)} H_{k,m}^Q(e_k, f_k, e_m, f_m) \leq U_k^Q \quad \forall k$$

$$V_k^L \leq \|(e_k, f_k)\| \leq V_k^U \quad \forall k.$$

Function F_k in the objective: convex quadratic

Complexity

Theorem (2011) Lavaei and Low: OPF is (weakly) NP-hard on trees.

Theorem (2014) van Hentenryck et al: OPF is NP-hard on trees.

Theorem (2007) B. and Verma (2009): OPF is strongly NP-hard on general graphs.

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Recent insight: use the SDP relaxation (Lavaei and Low, 2009 + many others)

$$\begin{aligned} \min \quad & \sum_k F_k \left(\sum_{\{k,m\} \in \delta(k)} H_{k,m}^P(e_k, f_k, e_m, f_m) \right) \\ \text{s.t.} \quad & L_k^P \leq \sum_{\{k,m\} \in \delta(k)} H_{k,m}^P(e_k, f_k, e_m, f_m) \leq U_k^P \quad \forall k \\ & L_k^Q \leq \sum_{\{k,m\} \in \delta(k)} H_{k,m}^Q(e_k, f_k, e_m, f_m) \leq U_k^Q \quad \forall k \\ & V_k^L \leq \|(e_k, f_k)\| \leq V_k^U \quad \forall k. \end{aligned}$$

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Reformulation of ACOPF:

$$\begin{aligned} \min \quad & F \bullet W \\ \text{s.t.} \quad & A_i \bullet W \leq b_i \quad i = 1, 2, \dots \\ & W \succeq 0, \quad W \text{ of rank } 1. \end{aligned}$$

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SDP Relaxation of OPF:

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$$\begin{aligned} \min \quad & F \bullet W \\ \text{s.t.} \quad & A_i \bullet W \leq b_i \quad i = 1, 2, \dots \\ & W \succeq 0. \end{aligned}$$

Fact: The SDP relaxation is often good! (“near” rank 1 solution).

But: the SDP relaxation is always slow on large graphs

- Real-life grids $\rightarrow > 10^4$ vertices
- SDP relaxation of OPF does not terminate

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Fact? Real-life grids have **small tree-width**

Definition 1: A graph has treewidth $\leq w$ if it has a chordal supergraph with clique number $\leq w + 1$

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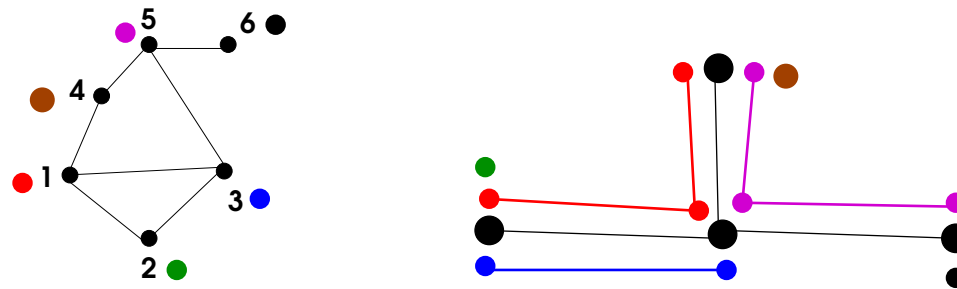
(Seymour and Robertson, late 1980s)

Tree-width

Let G be an undirected graph with vertices $V(G)$ and edges $E(G)$.

A tree-decomposition of G is a pair (T, Q) where:

- T is a tree. **Not** a subtree of G , just a tree
- For each vertex t of T , Q_t is a subset of $V(G)$. These subsets satisfy the two properties:
 - (1) For each vertex v of G , the set $\{t \in V(T) : v \in Q_t\}$ is a **subtree** of T , denoted T_v .
 - (2) For each edge $\{u, v\}$ of G , the two subtrees T_u and T_v **intersect**.
- The **width** of (T, Q) is $\max_{t \in T} |Q_t| - 1$.



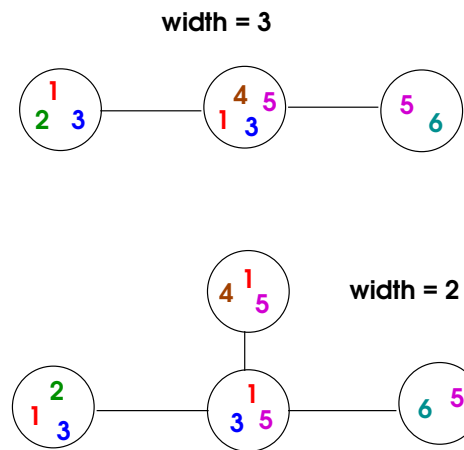
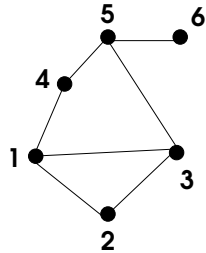
→ two subtrees T_u, T_v may overlap even if $\{u, v\}$ is **not** an edge of G

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Matrix-completion Theorem

gives fast SDP implementations:

Real-life grids with $\approx 3 \times 10^3$ vertices: \rightarrow 20 minutes runtime

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\rightarrow Perhaps low tree-width yields **direct** algorithms for ACOPF itself?

That is to say, not for a relaxation?

Much previous work using structured sparsity

- Bienstock and Özbay
- Wainwright and Jordan
- Grimm, Netzer, Schweighofer
- Laurent
- Lasserre et al
- Waki, Kim, Kojima, Muramatsu

older work ...

- Lauritzen (1996): tree-junction theorem
- Bertele and Brioschi (1972): nonserial dynamic programming
- Bounded tree-width in combinatorial optimization (too many authors)
- Fulkerson and Gross (1965): matrices with consecutive ones

ACOPF, again

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$$\begin{aligned}
 \min \quad & \sum_k F_k \left(\sum_{\{k,m\} \in \delta(k)} H_{k,m}^P(e_k, f_k, e_m, f_m) \right) \\
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$$\min \sum_k w_k$$

$$\text{s.t. } L_k^P \leq \sum_{\{k,m\} \in \delta(k)} H_{k,m}^P(e_k, f_k, e_m, f_m) \leq U_k^P \quad \forall k$$

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$$w_k = F_k \left(\sum_{\{k,m\} \in \delta(k)} H_{k,m}^P(e_k, f_k, e_m, f_m) \right) \quad \forall k$$

Graphical QCQP

Input: an undirected graph G .

- For every vertex k , a set of variables: $\{x_j : j \in I(k)\}$
- For every edge $e = \{k, m\}$, a quadratic

$$H_e(x) = H_e(\{x_j : j \in I(k) \cup I(m)\}).$$

- For now, the sets $I(k)$ are disjoint

$$\begin{aligned} \min \quad & \sum_k \sum_{j \in I(k)} c_{k,j} x_j \\ \text{s.t.} \quad & \sum_{e \in \delta(k)} H_e(x) \leq b_k \quad \forall k \\ & 0 \leq x_j \leq 1, \quad \forall j \end{aligned}$$

→ Easy to solve if graph has small tree-width?

Subset-sum problem

Input: positive integers p_1, p_2, \dots, p_n .

Problem: find a solution to:

$$\sum_{j=1}^n p_j x_j = \frac{1}{2} \sum_{j=1}^n p_j$$

$$x_j \in \{0, 1\}, \quad \forall j$$

(weakly) NP-hard (well...)

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$$x_j(1 - x_j) = 0, \quad \forall j$$

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This is a graphical QCQP on a **star** – so treewidth 1.

(Perhaps) approximate solutions?

$\{0, 1\}$ solutions with error $\left(\frac{1}{2} \sum_{j=1}^n p_j\right) \epsilon$ in time polynomial in ϵ^{-1} ?

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Graphical PCLP

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Density of a problem: size of **largest** set $I(k)$

Density of ACOPF problems: 3

Graphical, mixed-integer PCLP – or GMIPCLP

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Theorem 3

For any instance of **GMIPCLP** on a graph with **treewidth** w , **density** d , **max. degree** π , and any fixed $0 < \epsilon < 1$, there is a **linear program** of size (rows + columns) $O^*(\pi^{wd} \epsilon^{-w} n)$ whose feasibility and optimality error is $O(\epsilon)$
(abridged).

More general: MIPCLP (Basic polynomially-constrained mixed-integer LP)

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Theorem 2

For any instance of **MIPCLP** whose **intersection graph** has treewidth **w** , **max. degree** **π** , and any fixed **$0 < \epsilon < 1$** , there is a **linear program** of size (rows + columns) **$O^*(\pi^w \epsilon^{-w-1} n)$** whose feasibility and optimality error is **$O(\epsilon)$** (abridged).

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Intersection graph of a constraint system: (Fulkerson? (1962?))

- Has a **vertex** for every variable x_j
- Has an **edge** $\{x_i, x_j\}$ whenever x_i and x_j appear in the same constraint

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Two graphs:

- **G** , the graph of the instance
 - **H** , the intersection graph of the constraints
- Even if **G** has small treewidth, **H** might not

Example: subset sum problem. **G** is a **star**, **H** is a **clique**.

Theorem 0

Given an instance of graphical mixed-integer PCLP

- On a graph G of treewidth w ,
- with density d ,
- For every vertex k , a set of variables: $\{x_j : j \in I(k)\}$, for every edge $e = \{k, m\}$, a **polynomial**

$$P_e(x) = P_e(\{x_j : j \in I(k) \cup I(m)\}).$$

$$\begin{aligned} \min \quad & c^T x \\ \text{s.t.} \quad & \sum_{e \in \delta(k)} P_e(x) \leq b_k \quad \forall k \\ & x_j \in \{0, 1\}, \quad \forall j \in I, \quad 0 \leq x_j \leq 1, \quad \text{otherwise.} \end{aligned}$$

Density of a problem: size of **largest set** $I(k)$

There is an **equivalent**

mixed-integer polynomial optimization problem

whose **intersection graph** has tree-width $O(wd)$.

Theorem 0

Given an instance of graphical mixed-integer PCLP

- On a graph G of treewidth w ,
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There is an **equivalent mixed-integer polynomial optimization problem** whose **intersection graph** has tree-width $O(wd)$.

ACOPF problem on small treewidth graph \rightarrow (generalize)

Graphical QCQP on small treewidth graph and small density \rightarrow (generalize)

GMIPCLP on small treewidth graph and small density \rightarrow (generalize, reduce)

Mixed-integer PCLP with small treewidth intersection graph

Basic theorem:

There is a polynomial-time ϵ -approximate algorithm for such problems

Main technique: approximation through pure-binary problems

Glover, 1975 (abridged)

Let \mathbf{x} be a variable, with bounds $\mathbf{0} \leq \mathbf{x} \leq \mathbf{1}$. Let $\mathbf{0} < \gamma < \mathbf{1}$. Then we can approximate

$$\mathbf{x} \approx \sum_{h=1}^L 2^{-h} \mathbf{y}_h$$

where each \mathbf{y}_h is a **binary variable**. In fact, choosing $L = \lceil \log_2 \epsilon^{-1} \rceil$, we have

$$\mathbf{x} \leq \sum_{h=1}^L 2^{-h} \mathbf{y}_h \leq \mathbf{x} + \epsilon.$$

→ Given a mixed-integer polynomially constrained LP (MIPCLP), apply this technique to each continuous variable x_j

Mixed-integer polynomially-constrained LP:

$$\text{(P)} \quad \min \quad c^T x$$

$$\text{s.t.} \quad P_i(x) \leq b_i \quad 1 \leq i \leq m$$

$$x_j \in \{0, 1\} \quad \forall j \in I, \quad 0 \leq x_j \leq 1, \quad \text{otherwise}$$

substitute: $\forall j \notin I, \quad \mathbf{x}_j \rightarrow \sum_{h=1}^L 2^{-h} \mathbf{y}_{h,j}$, where each $\mathbf{y}_{h,j} \in \{0, 1\}$

$$L \approx \log_2 \epsilon^{-1}$$

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$$L \approx \log_2 \epsilon^{-1}$$

obtain **pure binary problem**:

$$\begin{aligned} \text{(Q)} \quad & \min \quad \hat{c}^T z \\ & \text{s.t.} \quad \hat{P}_i(z) \leq \hat{b}_i \quad 1 \leq i \leq m \\ & \quad \quad z_k \in \{0, 1\} \quad \forall k \end{aligned}$$

If **(P)** has intersection graph of treewidth \mathbf{w} ,
then **(Q)** has intersection graph of treewidth \mathbf{Lw} .

Mixed-integer polynomially-constrained LP:

$$\begin{aligned} \text{(P)} \quad & \min \quad c^T x \\ & \text{s.t.} \quad P_i(x) \leq b_i \quad 1 \leq i \leq m \end{aligned}$$

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Theorem

Consider a pure-binary PCLP with \mathbf{n} variables.

If the intersection graph has treewidth $\leq \mathbf{W}$ then there is an **exact** linear programming formulation with

$$\mathbf{O}(2^{\mathbf{W}} \mathbf{n}) \quad \text{variables and constraints.}$$

Conclusion

Given an ACOPF problem on a graph of treewidth $\leq w$ and n edges, and $0 \leq \epsilon \leq 1$ there is an LP formulation with the following properties:

- It has $O(\text{poly}(\epsilon^{-1})2^{O(w)}n)$ variables and constraints
- It produces ϵ -optimal and ϵ -feasible solutions.

Talk on Friday by Gonzalo on the pure-binary problems.