

## Background

### Generalized Disjunctive Program (GDP) <sup>1-4</sup>

$$\min_{\mathbf{x}, \mathbf{Y}} f(\mathbf{x})$$

$$\text{s.t. } \mathbf{g}(\mathbf{x}) \leq 0,$$

$$\bigvee_{i \in D_k} \left[ h_{ik}(\mathbf{x}) \leq 0 \right], \quad \forall k \in K,$$

$$\bigvee_{i \in \bar{D}_k} Y_{ik}, \quad \forall k \in K,$$

$$\Omega(\mathbf{Y}) = \text{True},$$

$$\mathbf{x}^l \leq \mathbf{x} \leq \mathbf{x}^u,$$

$$\mathbf{x} \in \mathbb{R}^n,$$

$$Y_{ik} \in \{\text{False}, \text{True}\}, \quad \forall k \in K, i \in D_k.$$

### Hull reformulation of GDP

$$\min_{\mathbf{x}, \mathbf{y}} f(\mathbf{x})$$

$$\text{s.t. } \mathbf{g}(\mathbf{x}) \leq 0,$$

$$\sum_{i \in D_k} y_{ik} = 1 \quad \forall k \in K,$$

$$\mathbf{E}\mathbf{y} \geq \mathbf{e},$$

$$\mathbf{x} = \sum_{i \in D_k} \mathbf{v}_{ik}, \quad k \in K$$

$$\left( \text{cl } \tilde{h}_{ik} \right) (\mathbf{v}_{ik}, y_{ik}) \leq 0, \quad k \in K, i \in D_k$$

$$\mathbf{v}_{ik} \in \mathbb{R}^n, \quad k \in K, i \in D_k$$

$$\mathbf{x}^l \leq \mathbf{x} \leq \mathbf{x}^u,$$

$$\mathbf{x} \in \mathbb{R}^n,$$

$$y_{ik} \in \{0, 1\} \quad \forall k \in K, i \in D_k.$$

To calculate numerically the closure of a perspective function, an  $\varepsilon$ -approximation method (where  $\varepsilon$  is a small number, i.e.  $10^{-4}$ ) proposed by Furman, Sawaya, and Grossmann <sup>5</sup> is typically employed:

$$\left( \text{cl } \tilde{h} \right) (\mathbf{v}, y) \approx ((1 - \varepsilon)y + \varepsilon) h \left( \frac{\mathbf{v}}{(1 - \varepsilon)y + \varepsilon} \right) - \varepsilon h(0)(1 - y),$$

For the quadratic function  $h(\mathbf{v}) = \mathbf{v}^T Q \mathbf{v} + \mathbf{c}^T \mathbf{v} + d$ , where  $Q \in \mathbb{R}^{n \times n}$ ,  $\mathbf{c} \in \mathbb{R}^n$ , and  $d \in \mathbb{R}$ , after simplification, an  $\varepsilon$ -approximation results in a general non-linear function:

$$\left( \text{cl } \tilde{h} \right) (\mathbf{v}, y) \approx \frac{\mathbf{v}^T Q \mathbf{v}}{(1 - \varepsilon)y + \varepsilon} + \mathbf{c}^T \mathbf{v} + dy$$

Two Feasible Regions + Exact Hull relaxation &  $\varepsilon$ -approximations

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## Computational experiments

### 240 Convex random instances ( $Q \succeq 0$ ):

 $3 \leq |K| \leq 10, \quad 10 \leq |D_k| \leq 15, \quad |J_{ik}| = 10, \quad 3 \leq n \leq 7$

#### Gurobi

#### Baron

#### SCIP

### 100 Non-convex random instances:

 $3 \leq |K| \leq 10, \quad 10 \leq |D_k| \leq 15, \quad |J_{ik}| = 10, \quad 3 \leq n \leq 9$

#### Gurobi

#### Baron

#### SCIP

## Exact Hull Reformulation of Quadratic GDP

Disjunctions of quadratically constrained GDP can be expressed as follows:

$$\bigvee_{i \in D_k} \left[ \mathbf{x}^T Q_{jik} \mathbf{x} + \mathbf{c}_{jik}^T \mathbf{x} + d_{jik} \leq 0, j \in J_{ik} \right], \quad k \in K$$

We propose the following reformulations:

### Conic Exact Hull Reformulation (CEHR) for convex constraints:

$$\mathbf{x} = \sum_{i \in D_k} \mathbf{v}_{ik},$$

$$\mathbf{x}^l y_{ik} \leq \mathbf{v}_{ik} \leq \mathbf{x}^u y_{ik},$$

$$\mathbf{v}_{ik}^T Q_{jik} \mathbf{v}_{ik} \leq t_{jik} y_{ik},$$

$$t_{jik} + \mathbf{c}_{jik}^T \mathbf{v}_{ik} + d_{jik} y_{ik} \leq 0,$$

$$\mathbf{v}_{ik} \in \mathbb{R}^n, \quad t_{jik} \in \mathbb{R}_+.$$

### General Exact Hull Reformulation (GEHR) for nonconvex constraints:

$$\mathbf{x} = \sum_{i \in D_k} \mathbf{v}_{ik},$$

$$\mathbf{v}_{ik}^T Q_{jik} \mathbf{v}_{ik} + \mathbf{c}_{jik}^T \mathbf{v}_{ik} y_{ik} + d_{jik} y_{ik}^2 \leq 0,$$

$$\mathbf{x}^l y_{ik} \leq \mathbf{v}_{ik} \leq \mathbf{x}^u y_{ik},$$

$$\mathbf{v}_{ik} \in \mathbb{R}^n.$$

where  $k \in K$  indexes disjunctions,  $i \in D_k$  indexes disjuncts in disjunction  $k$ , and  $j \in J_{ik}$  indexes quadratic constraints in disjunct  $i$ . Here,  $\mathbf{v}_{ik}$  is the disaggregated variable,  $y_{ik}$  is the disjunct indicator, and  $Q_{jik}$ ,  $\mathbf{c}_{jik}$ , and  $d_{jik}$  are the quadratic, linear, and constant coefficients.

## Computational experiments

Computational experiments were conducted on various convex and non-convex quadratic GDPs, such as random convex and non-convex quadratic GDPs, convex k-means clustering, a non-convex CSTR network benchmark, and constrained layout instances.

### Solver outcomes across reformulation strategies for convex random quadratic GDPs

Strategy	Optimal	Timeout	Infeasible	Objective mismatch	Total
<b>Solver: Gurobi</b>					
BigM	91	9	0	0	100
Hull $\varepsilon$ -approx. ( $\varepsilon = 10^{-4}$ )	2	86	0	12	100
GEHR	59	41	0	0	100
CEHR	7	86	0	7	100
Binary Mult.	83	17	0	0	100
<b>Solver: BARON</b>					
BigM	95	4	0	1	100
Hull $\varepsilon$ -approx. ( $\varepsilon = 10^{-4}$ )	0	99	1	0	100
GEHR	7	86	0	7	100
Binary Mult.	88	12	0	0	100
<b>Solver: SCIP</b>					
BigM	91	9	0	0	100
Hull $\varepsilon$ -approx. ( $\varepsilon = 10^{-4}$ )	11	89	0	0	100
GEHR	41	59	0	0	100
Binary Mult.	39	61	0	0	100

Strategy	Optimal	Timeout	Infeasible	Objective mismatch	Total
<b>Solver: Gurobi</b>					
BigM	240	0	0	0	240
Hull $\varepsilon$ -approx. ( $\varepsilon = 10^{-4}$ )	2	0	200	38	240
GEHR	240	0	0	0	240
CEHR	240	0	0	0	240
Binary Mult.	167	73	0	0	240
<b>Solver: BARON</b>					
BigM	233	7	0	0	240
Hull $\varepsilon$ -approx. ( $\varepsilon = 10^{-4}$ )	5	233	0	2	240
GEHR	29	183	0	28	240
CEHR	20	190	0	30	240
Binary Mult.	180	60	0	0	240
<b>Solver: SCIP</b>					
BigM	240	0	0	0	240
Hull $\varepsilon$ -approx. ( $\varepsilon = 10^{-4}$ )	47	182	0	11	240
GEHR	104	136	0	0	240
CEHR	240	0	0	0	240
Binary Mult.	94	146	0	0	240
<b>Solver: SCIP (convex flag)</b>					
BigM	240	0	0	0	240
Hull $\varepsilon$ -approx. ( $\varepsilon = 10^{-4}$ )	238	0	0	2	240
GEHR	4	0	217	19	240
CEHR	240	0	0	0	240
Binary Mult.	0	0	219	21	240

## Conclusion

- **Exact Hull Reformulation:** The proposed exact hull reformulation offers practical benefits by preserving the original quadratic problem structure and eliminating approximations in GDPs
- **Improved Solver Performance:** Numerical experiments show that state-of-the-art Mixed-Integer Nonlinear Programming (MINLP) solvers solve the proposed reformulations faster and more reliably than  $\varepsilon$ -approximation-based approaches.
- **Value of Customization:** Results highlight the importance of developing tailored, exact reformulations, especially when constraints exhibit simpler structural forms.

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