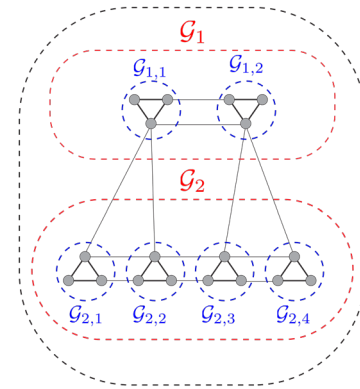
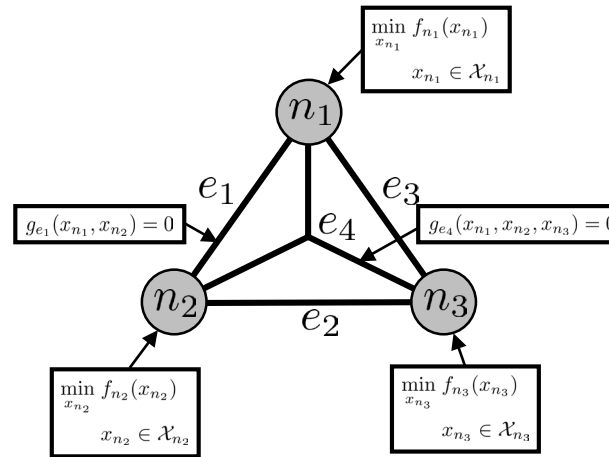




WISCONSIN
UNIVERSITY OF WISCONSIN-MADISON



Graph-Based Decomposition Approaches through PlasmO.jl

David L. Cole and Victor M. Zavala

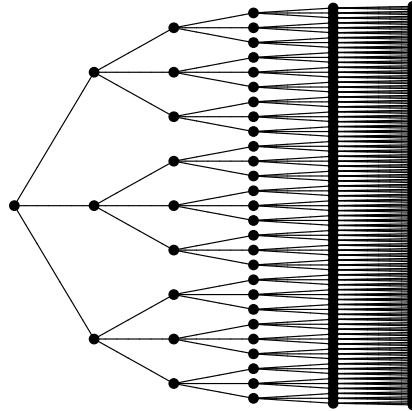
Department of Chemical and Biological Engineering
University of Wisconsin-Madison

Power of Abstraction

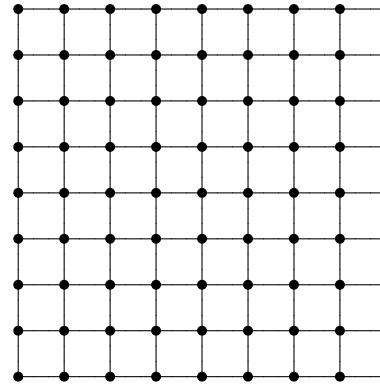
Dynamic Optimization



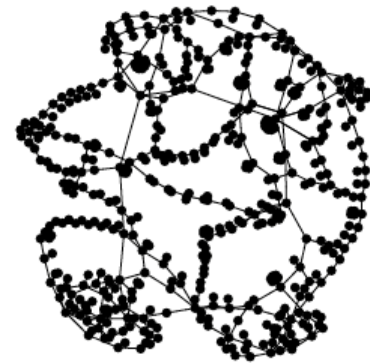
Stochastic Optimization



PDE Optimization



Network Optimization



- Graphs can be used to represent different optimization formulations

$$\begin{aligned} \min f(\mathbf{x}) \\ \text{s.t. } \mathbf{x} \in \mathcal{X} \\ g(\mathbf{x}) = 0 \end{aligned}$$



Plasmo.jl OptiGraph, $\mathcal{G}(\mathcal{N}, \mathcal{E})$

$$\begin{aligned} \min \sum_{n \in \mathcal{N}(\mathcal{G})} f_x(x_n) \\ \text{s.t. } x_n \in \mathcal{X}_n, \quad n \in \mathcal{N}(\mathcal{G}) \quad \text{node constraints} \\ g_e(\{x_n\}_{n \in \mathcal{N}(e)}) = 0, \quad e \in \mathcal{E}(\mathcal{G}) \quad \text{edge/link constraints} \end{aligned}$$

- Uses a unifying abstraction called an OptiGraph, containing OptiNodes and OptiEdges
- OptiNodes contain variables, objectives, constraints; OptiEdges contain linking constraints

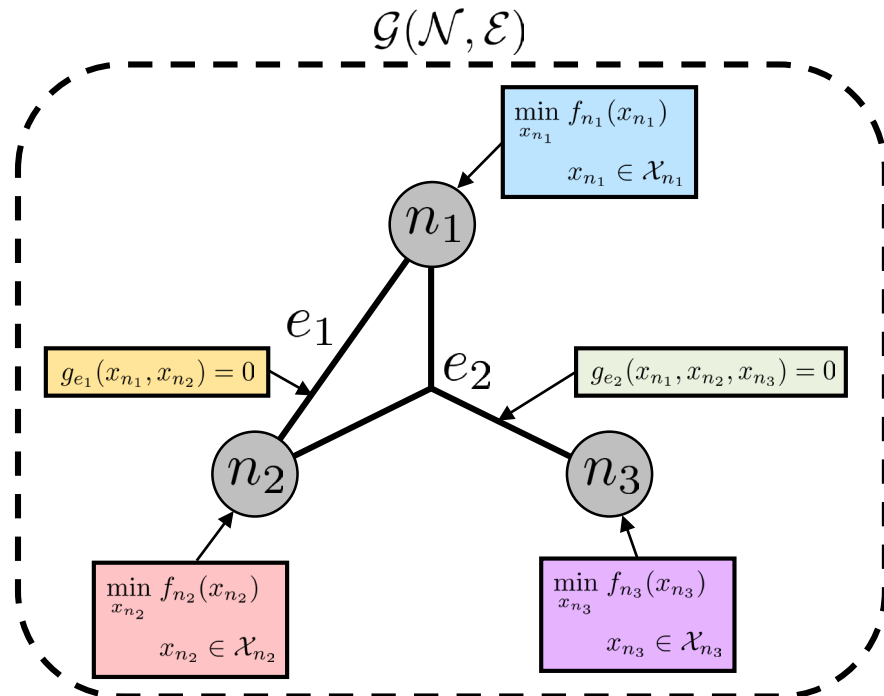
$$\begin{aligned} \min & f(\mathbf{x}) \\ \text{s.t. } & \mathbf{x} \in \mathcal{X} \\ & g(\mathbf{x}) = 0 \end{aligned}$$



Plasmo.jl OptiGraph, $\mathcal{G}(\mathcal{N}, \mathcal{E})$

$$\begin{aligned} \min & \sum_{n \in \mathcal{N}(\mathcal{G})} f_x(x_n) \\ \text{s.t. } & x_n \in \mathcal{X}_n, \quad n \in \mathcal{N}(\mathcal{G}) \quad \text{node constraints} \\ & g_e(\{x_n\}_{n \in \mathcal{N}(e)}) = 0, \quad e \in \mathcal{E}(\mathcal{G}) \quad \text{edge/link constraints} \end{aligned}$$

$$\begin{aligned} \min & f_{n_1}(x_{n_1}) + f_{n_2}(x_{n_2}) + f_{n_3}(x_{n_3}) \\ \text{s.t. } & g_{e_1}(x_{n_1}, x_{n_2}) = 0 \\ & g_{e_2}(x_{n_1}, x_{n_2}, x_{n_3}) = 0 \\ & x_{n_1} \in \mathcal{X}_{n_1} \\ & x_{n_2} \in \mathcal{X}_{n_2} \\ & x_{n_3} \in \mathcal{X}_{n_3} \end{aligned}$$



- Uses a unifying abstraction called an OptiGraph, containing OptiNodes and OptiEdges
- OptiNodes contain variables, objectives, constraints; OptiEdges contain linking constraints

```
1 using Plasmo, Ipopt
```

- Plasmo extends JuMP.jl and provides easy, user-friendly interface

Modular and Hierarchical Model Building

```

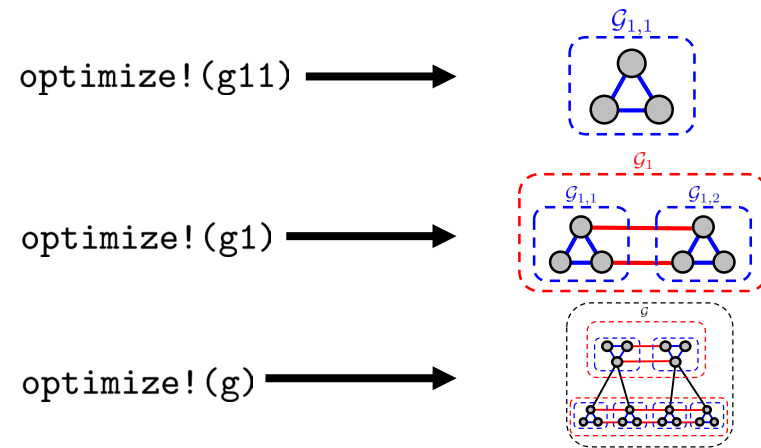
1  g11 = OptiGraph()
2
3  @optinode(g11, ....)
4  @variable(....)
5  @constraint(....)
6  @linkconstraint(g11, ....)
    
```

```

1  g1 = OptiGraph()
2  g11 = OptiGraph()
3  ....
4  g12 = OptiGraph()
5  ....
6  add_subgraph!(g1, g11)
7  add_subgraph!(g1, g12)
8  add_linkconstraint(g1, ....)
    
```

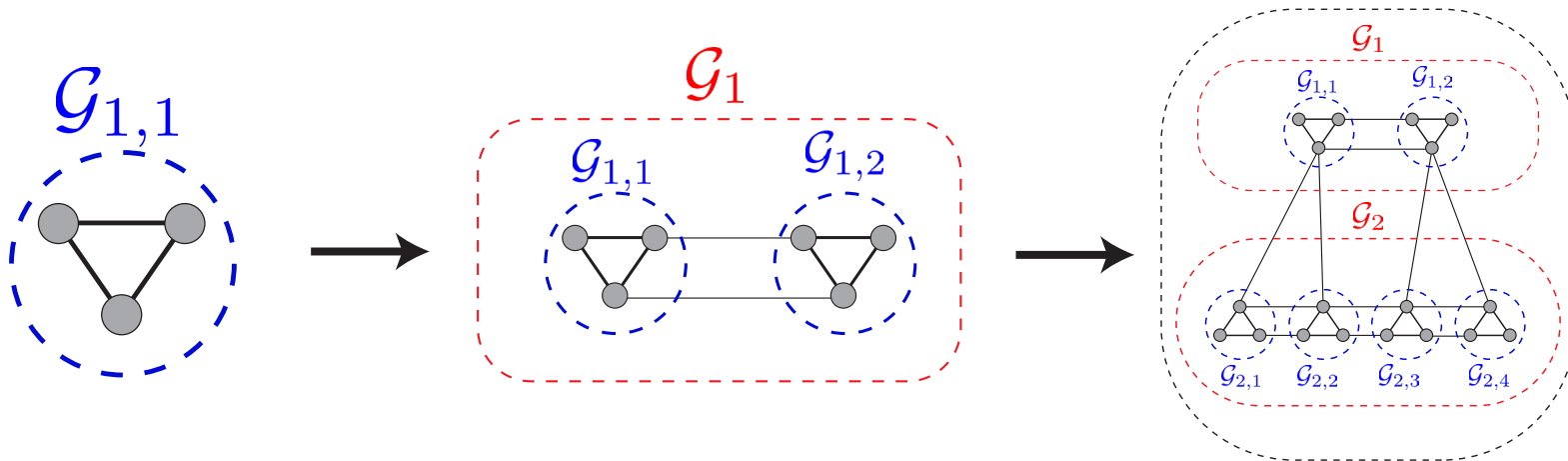
```

1  g = OptiGraph()
2
3  g1 = OptiGraph()
4  ....
5  add_subgraph!(g1, g11)
6  add_subgraph!(g1, g12)
7
8  g2 = OptiGraph()
9  ....
10 add_subgraph!(g2, g21)
11 add_subgraph!(g2, g22)
12 add_subgraph!(g2, g23)
13 add_subgraph!(g2, g24)
14
15 add_subgraph!(g, g1)
16 add_subgraph!(g, g2)
17 add_linkconstraint(g, ....)
    
```



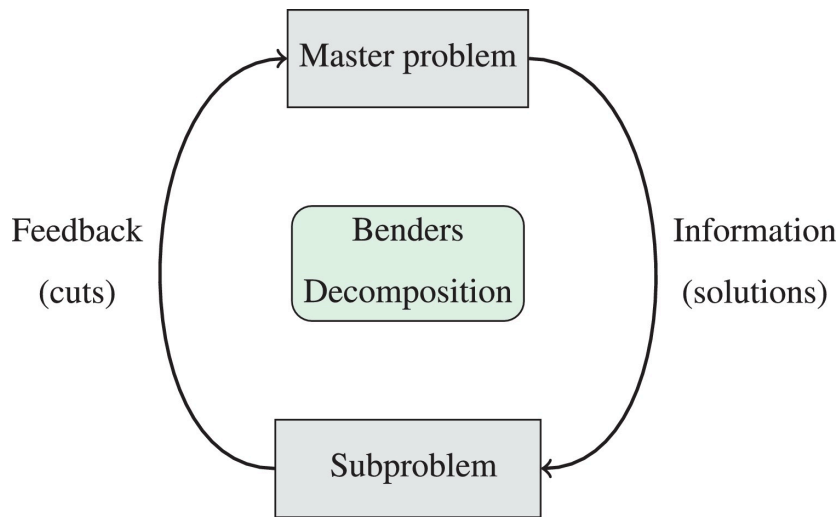
- Graphs can be “nested” as subgraphs within other graphs
- Subgraphs enable modular and hierarchical construction of models
- Each subgraph can be treated as independent optimization problems

- More subgraph-centric, better memory usage
- No longer uses `@NLconstraint`, `@NLobjective`, `@NLexpression`
- `LinkConstraintRef` is replaced by a standard MOI constraint
- Hypergraph structure no longer stored internally

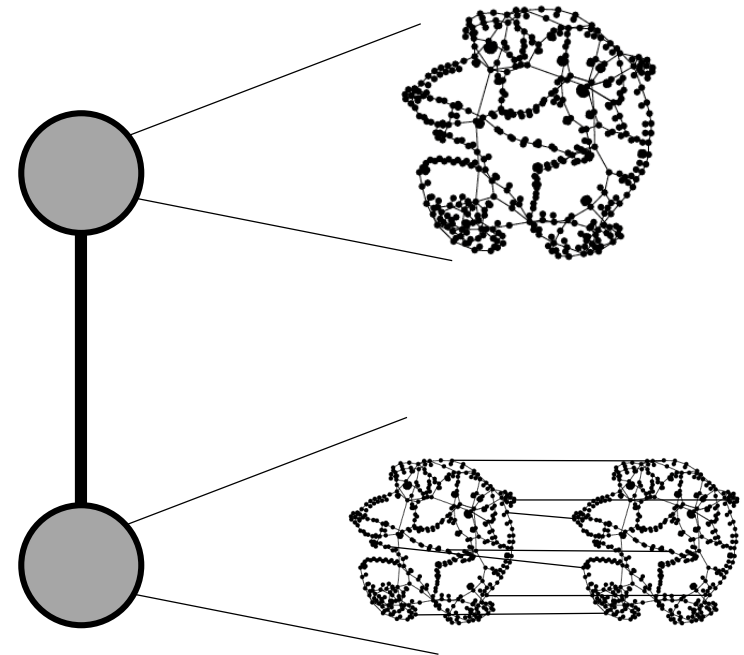


Plasmo.jl Creates Decomposable Structures

Benders Decomposition

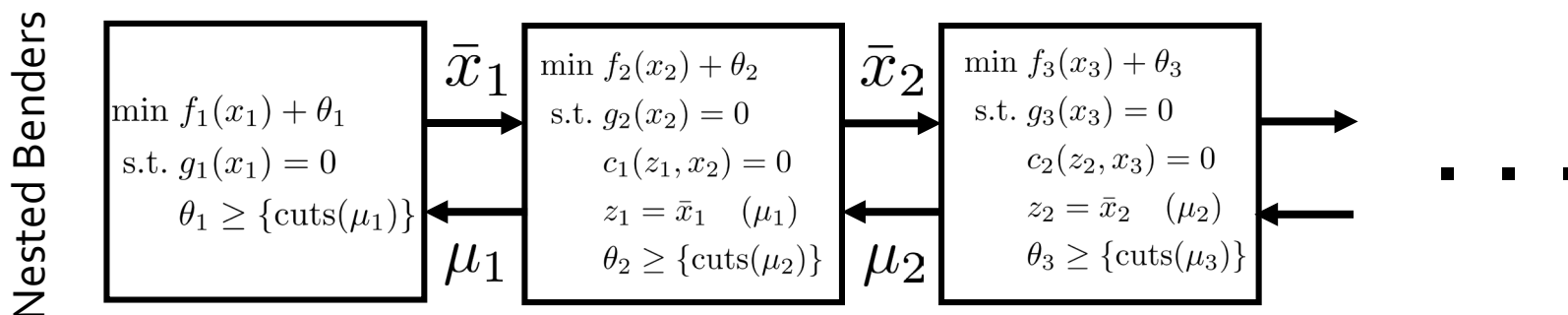
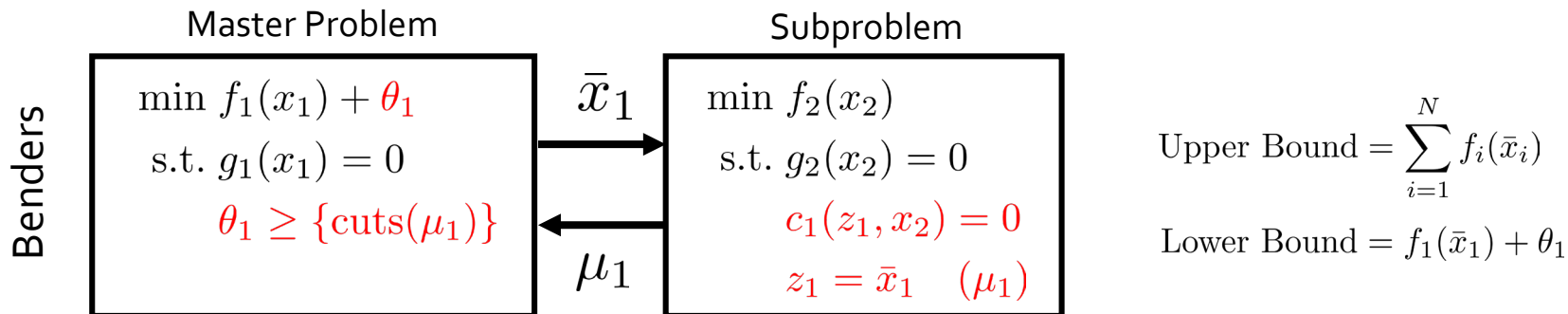
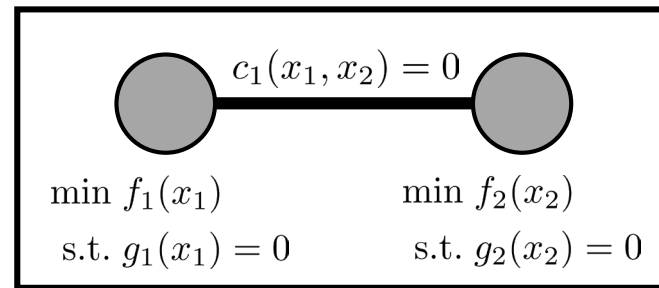


Graph Representation



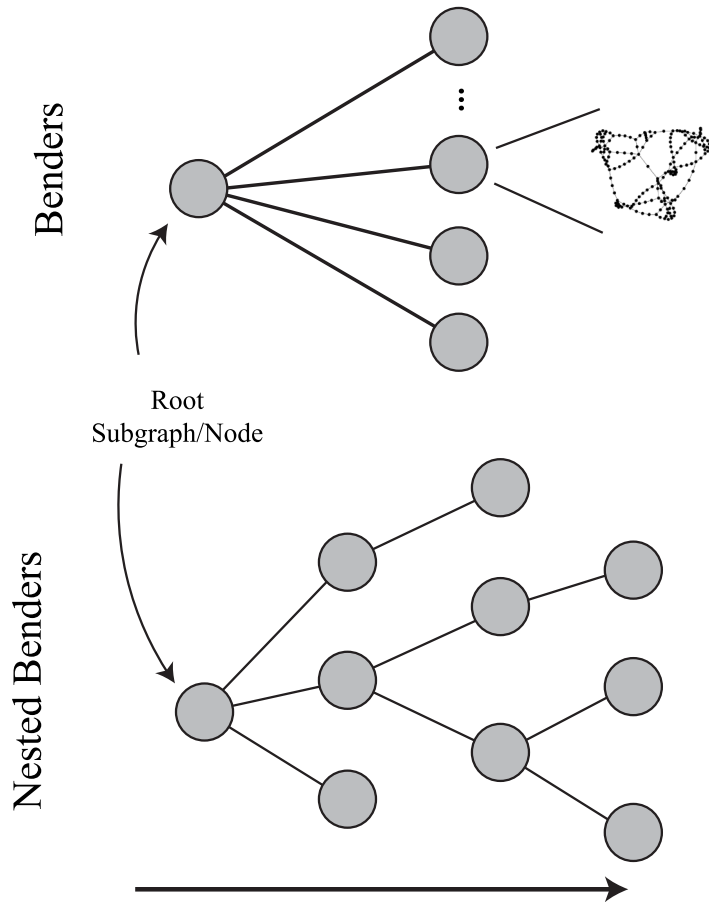
- Benders decomposition (left) can be generalized to a graph structure
- Graphs can provide a basis for applying decomposition schemes

Benders Decomposition Strategy



- θ = cost-to-go – lower bound on subproblem objective
- Problems solved sequentially, duals passed backwards for cuts

PlasmoDecompositions.jl



Master/Root Problem

Subproblem

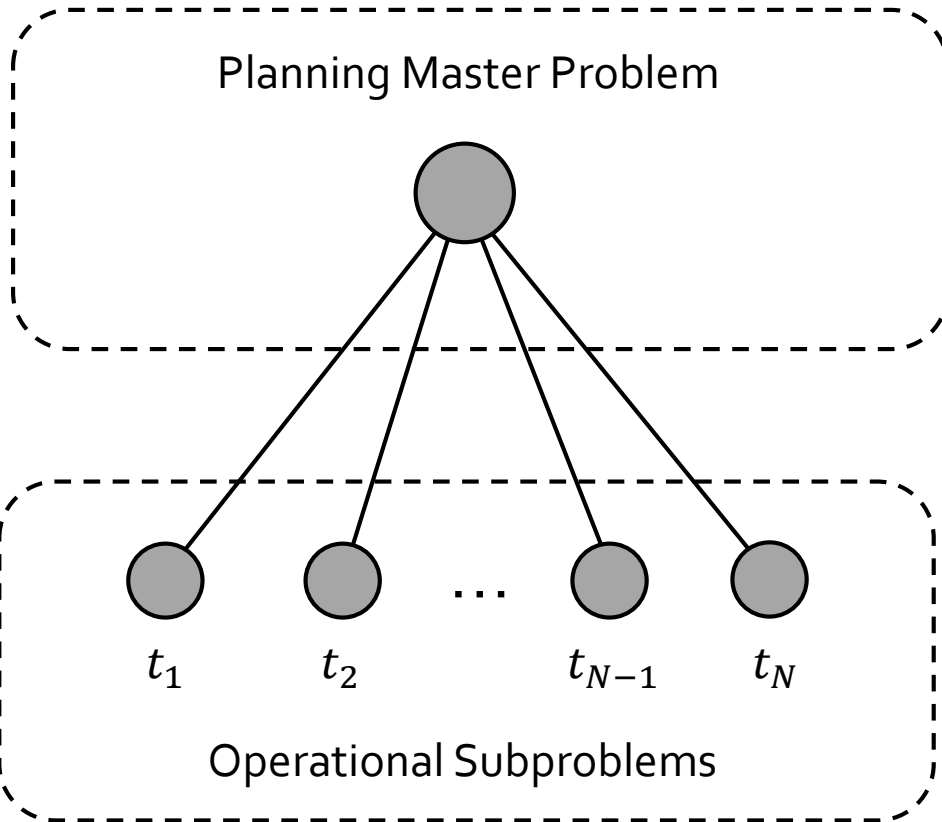
$$\begin{array}{ccc}
 \text{Master/Root Problem} & \xrightarrow{c(x_1, x_2) = 0} & \text{Subproblem} \\
 \min f_1(x_1) & & \min f_2(x_2) \\
 \text{s.t. } g_1(x_1) \geq 0 & & \text{s.t. } g_2(x_2) \geq 0
 \end{array}$$

PlasmoDecompositions.jl

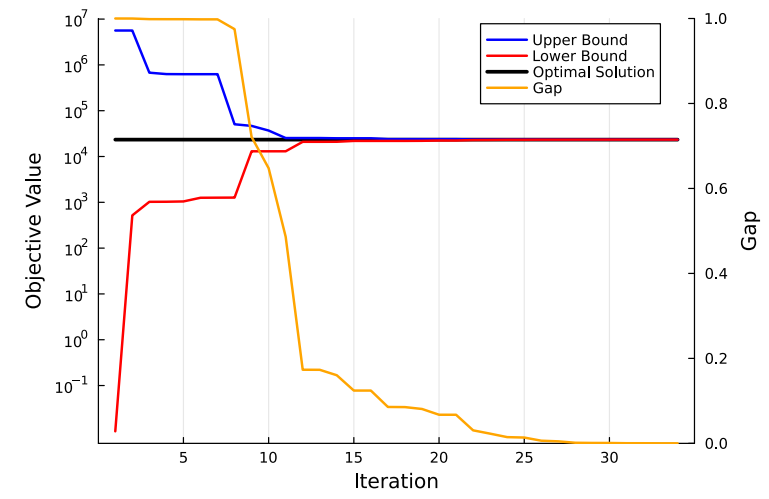
$$\begin{array}{ccc}
 \min f_1(x_1) + \theta & \xrightarrow{\quad} & \min f_2(x_2) \\
 \text{s.t. } g_1(x_1) \geq 0 & & \text{s.t. } g_1(x_1) \geq 0 \\
 \theta \geq \{\text{cuts}(\mu_1)\} & & c(z_1, x_2) = 0 \\
 & & z_1 = \hat{x}_1 \quad (\mu_1)
 \end{array}$$

- PlasmoDecompositions.jl takes overall graph and root/master problem as arguments
- Detects links, adds cost-to-go/cuts, performs forward/backward passes
- Graphs are *agnostic* to a domain (e.g., temporal/spatial)

Example: Benders for Capacity Expansion

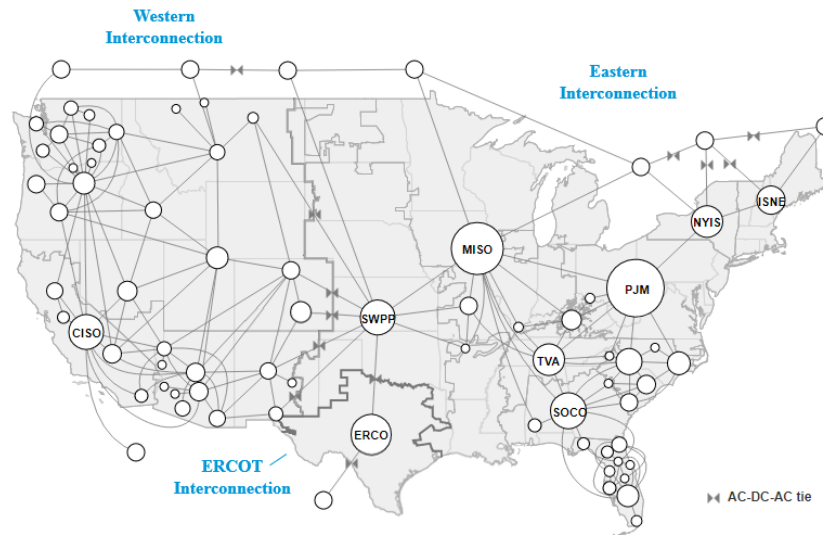


```
1 using PlasmDecompositions
2 ddopt = DDPoptimizer(
3     g,
4     master_graph,
5     regularize = true,
6     multicut = true,
7     add_slacks = false,
8     parallelize_benders = true,
9     strengthened = true,
10    tol = 1e-4
11 )
12 JuMP.optimize!(ddopt)
```



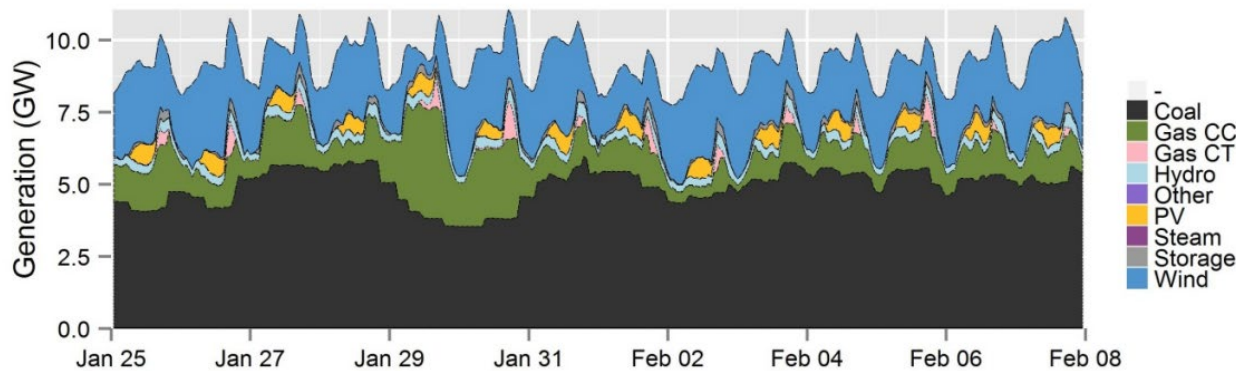
- Proof of Concept Example: ~120k variables, 11 subproblem graphs
- Subproblems are independent and can be solved in parallel
- Overall solution time was the same as w/o decomposition when using HiGHS

Example: Production Cost Modeling (PCM)



US Energy Information Administration, Hourly Electric Grid Monitor

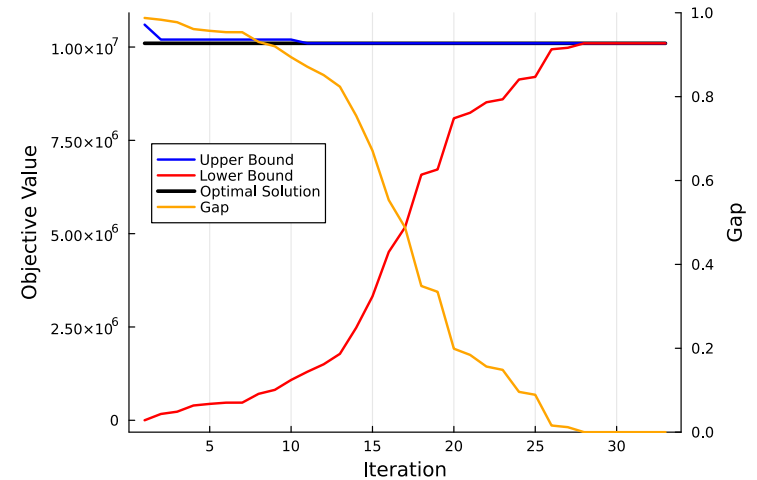
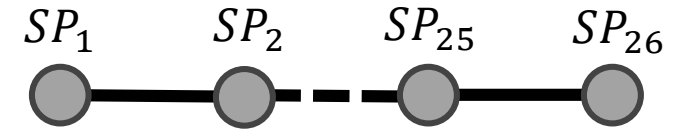
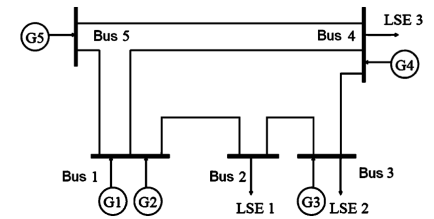
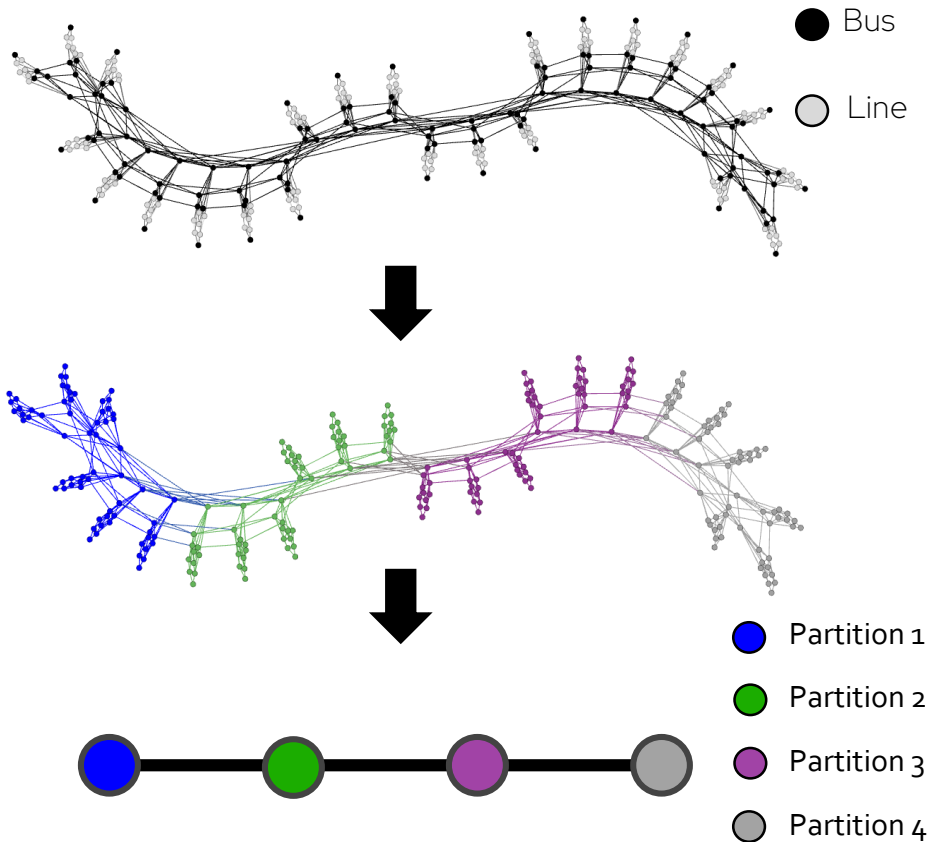
min	Start-Up/Shut-Down Costs + Operation Costs
s.t.	Start-Up Constraints Shut-Down Constraints Ramp Up/Down Constraints Capacity Constraints Transmission Constraints Battery Constraints



Barrows et al., 2014. NREL/TP-6A20-60969

- MIP for determining cost of operating a power network
- PCM minimizes costs of generator startup, shutdown, and operation

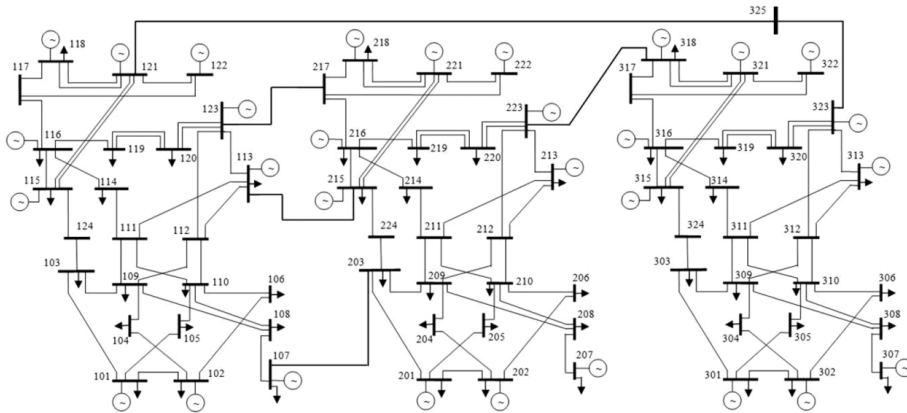
PCM – 5-Bus System as an OptiGraph



	NBD	Gurobi	
Gap	0.20%	0.95%	0.50 %
Solve Time (min)	58	43	240
Max Memory (GB)	14.4	42.3	44.2

- Graph can be aggregated to create tree structure
- 52-week problem solved with Nested Benders (NBD) using 26 subproblems (2 weeks each)
- NBD used less than half the memory of Gurobi, and required less time to solve

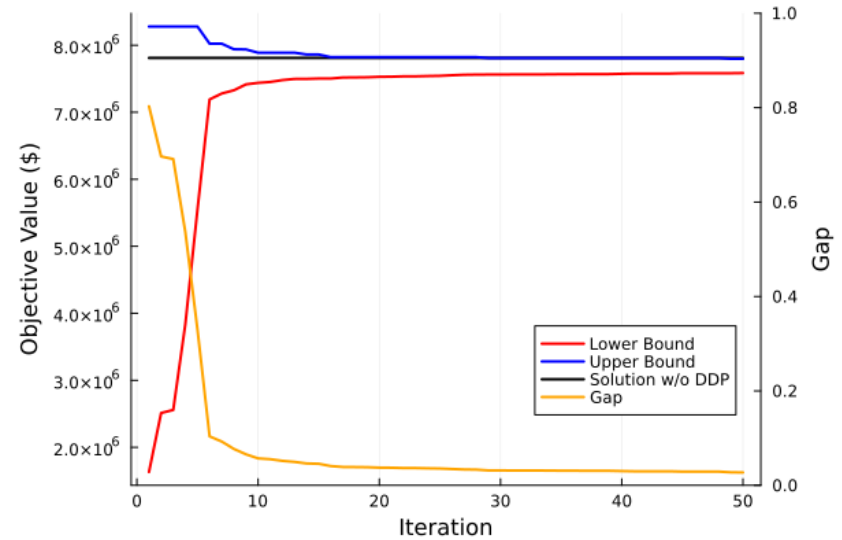
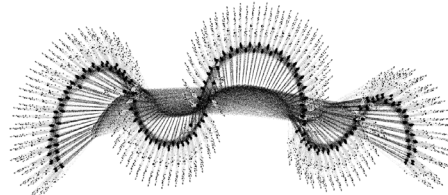
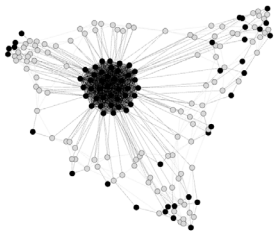
PCM – 73-Bus System as an OptiGraph



Gonzalez-Fernandez et al., *IEEE Trans. Power Syst.* 28, 4598–4606 (2013).

1 Time Point

31-day problem (with aggregation)

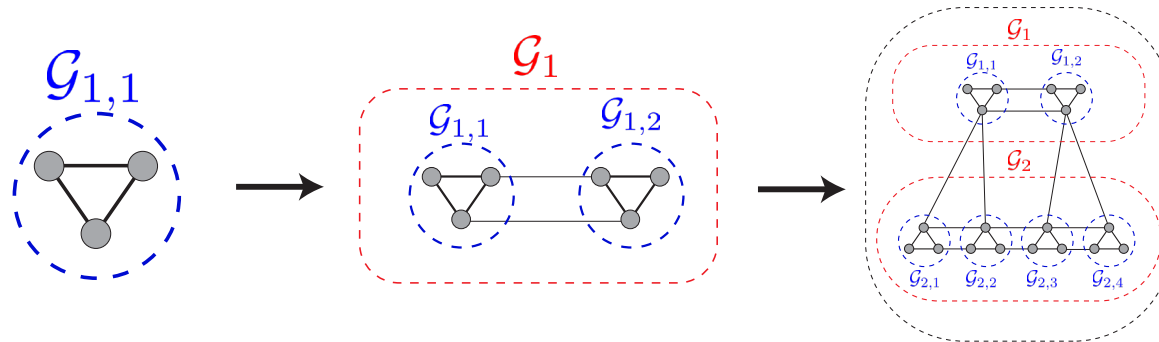


	NBD	Xpress
Gap	2.7%	1.2%
Objective Value	\$7.798e6	\$7.810e6
Solve Time (hr)	34.8	11.5
Max Memory (GB)	74	180

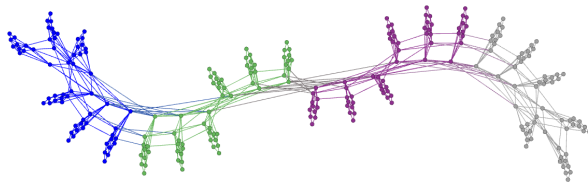
- 73-bus system has higher complexity of optimization and structure
- Solving with NBD over 31-day total horizon required less overall memory
- Decomposition enables use of non-commercial solvers

Conclusions and Future Work

- Graphs/Plasmo.jl give a general framework for structured optimization

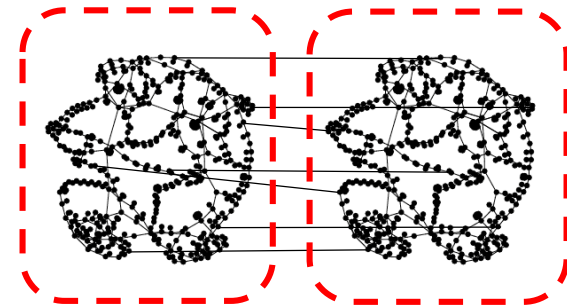
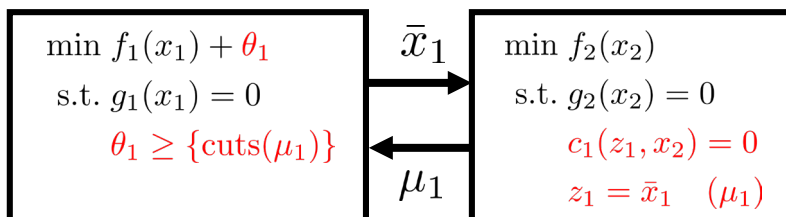


- PlasmoDecompositions.jl facilitates scalable decomposition strategies



	DDP	Gurobi	
Gap	0.20%	0.95%	0.50 %
Solve Time (min)	58	43	240
Max Memory (GB)	14.4	42.3	44.2

- Graphs can help identifying application of decomposition schemes



Acknowledgements



Dr. Victor
Zavala



Dr. Jordan
Jalving



Dr. Harsha
Gangammanavar



Dr. Omar José
Guerra-Fernandez

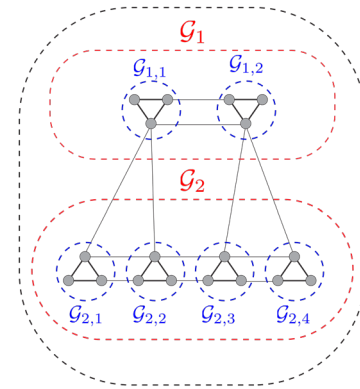
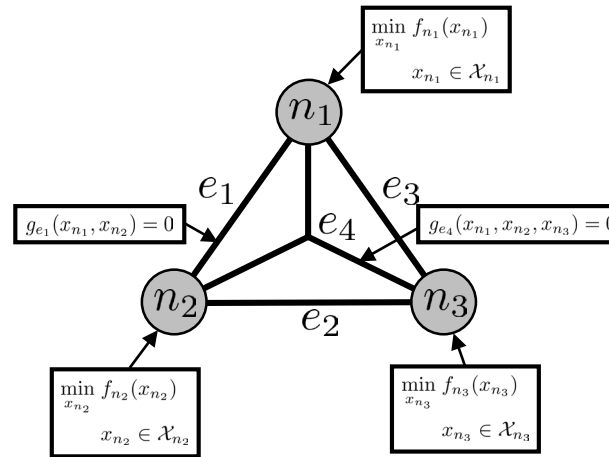
- Cole, D.L., Gangammanavar, H., and Zavala, V.M. 2023. Hierarchical graph modeling for multi-scale optimization of power systems. arXiv:2309.10568
- Cole, D.L. and Zavala, V.M., 2024. PlasmaData.jl – a Julia framework for modeling and analyzing complex data as graphs. arXiv:2401.11404
- Github: dlcole3
- Email: dlcole3@wisc.edu



This material is based upon work supported by the National Science Foundation under award CBET-1748516.



WISCONSIN
UNIVERSITY OF WISCONSIN-MADISON



Graph-Based Decomposition Approaches through Plasmojl

David L. Cole and Victor M. Zavala

Department of Chemical and Biological Engineering
University of Wisconsin-Madison