



# **Models and Computational Strategies for Multistage Stochastic Programming under Endogenous and Exogenous Uncertainties**

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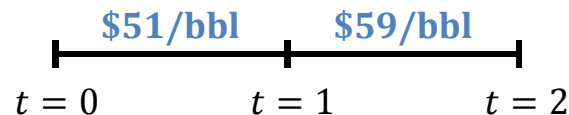
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# Types of Uncertainty

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- Classified by the way the uncertainty is resolved: **exogenous** or **endogenous** (Jonsbråten, 1998)
- **Exogenous uncertainty**
  - ❑ Parameter values **revealed independently of operation decisions**
  - ❑ Realizations occur automatically in each time period
  - ❑ **Market uncertainty** (e.g., crude-oil prices)



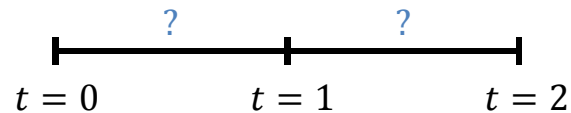
- **Endogenous uncertainty**
  - ❑ Realizations are **affected by operation decisions**
  - ❑ Two distinct types: **Type 1** and **Type 2** (Goel and Grossmann, 2006)

# Types of Uncertainty

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➤ **Type-2 endogenous uncertainty (Goel and Grossmann, 2006)**

- ❑ Decisions affect the **timing of realizations**
- ❑ A parameter is Type-2 endogenous if its **true value cannot be determined until a decision is made**
- ❑ These are technical parameters that represent **intrinsic properties of a given source** (e.g., size of an oilfield)
- ❑ Not associated with a particular time period

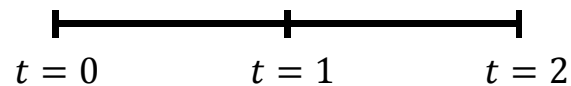


- ❑ We will be focusing on **exogenous** and **Type-2 endogenous uncertainties**

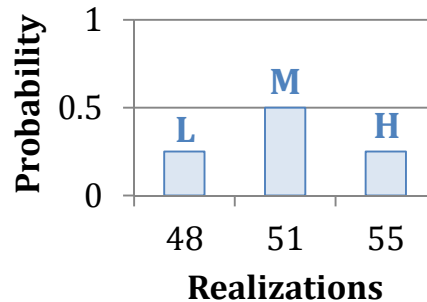
# Stochastic Programming

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- **Stochastic programming** is a scenario-based framework for optimization under uncertainty (Birge and Louveaux, 2011)
- Two assumptions:
  - ❑ Time horizon is represented by a set of **discrete time points**

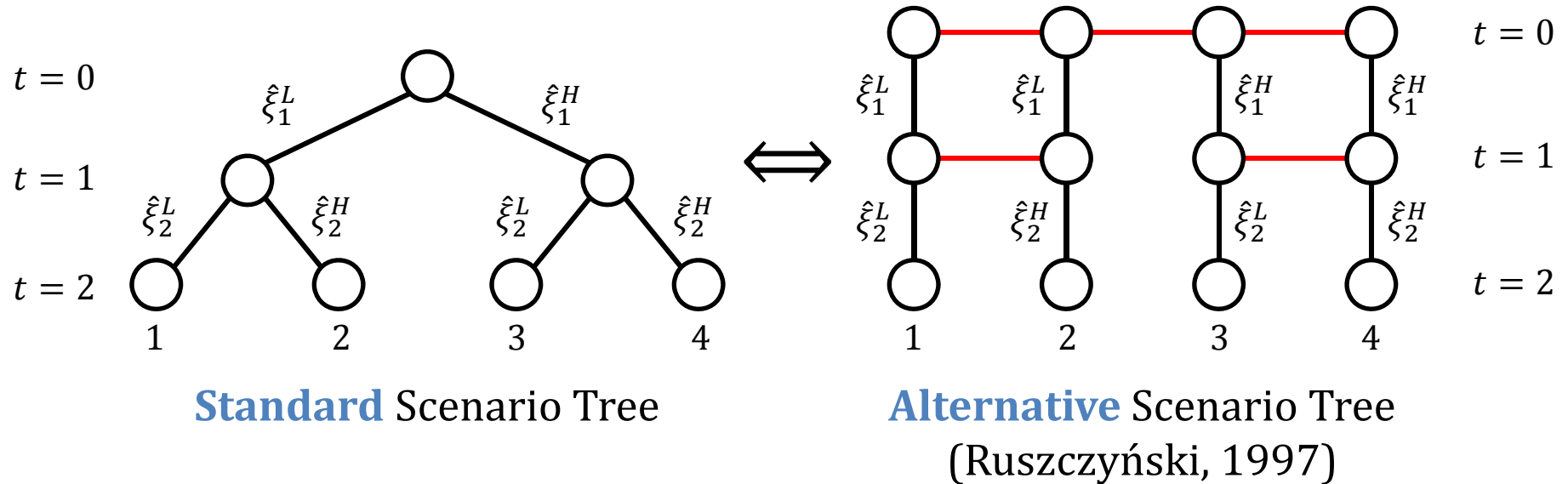


- ❑ Uncertain parameters are described by a **discretized probability distribution**



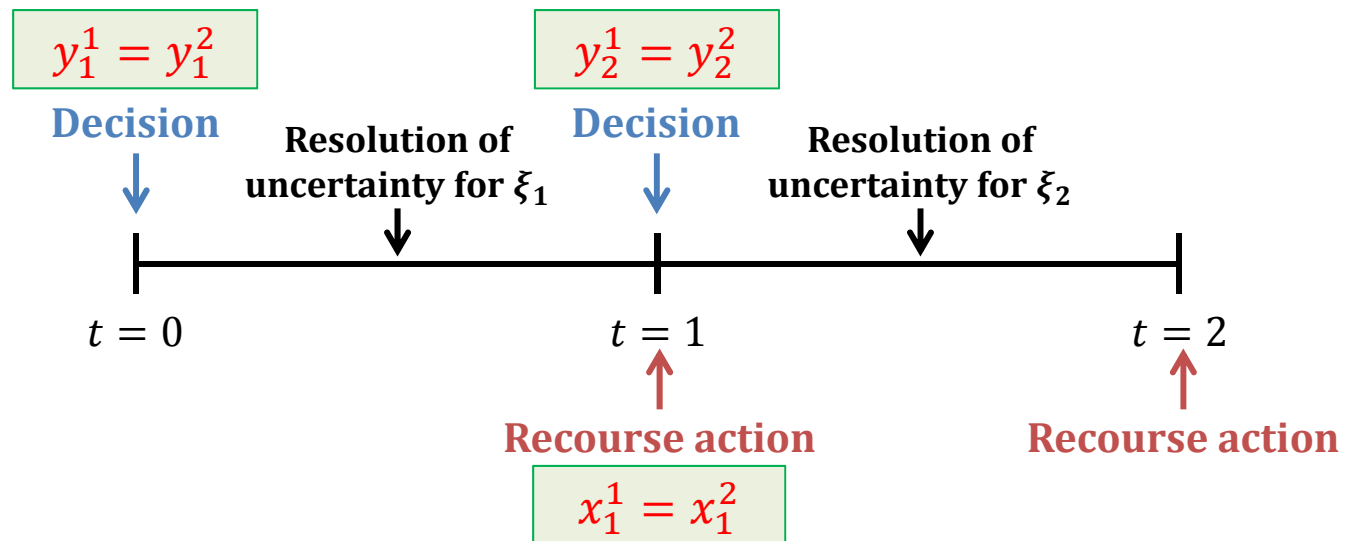
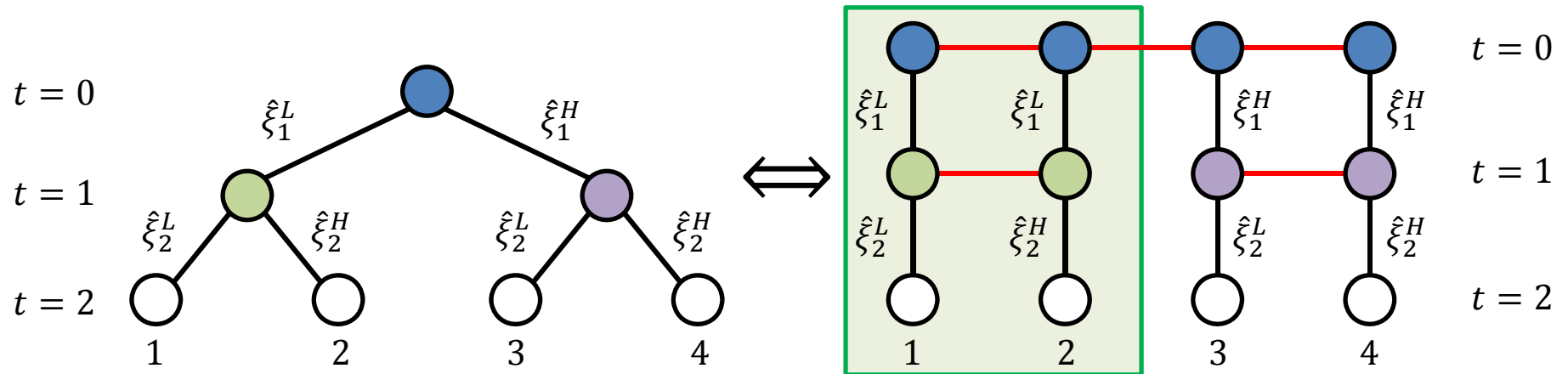
- This allows us to model stochastic processes with **scenario trees**

# MSSP under Exogenous Uncertainty

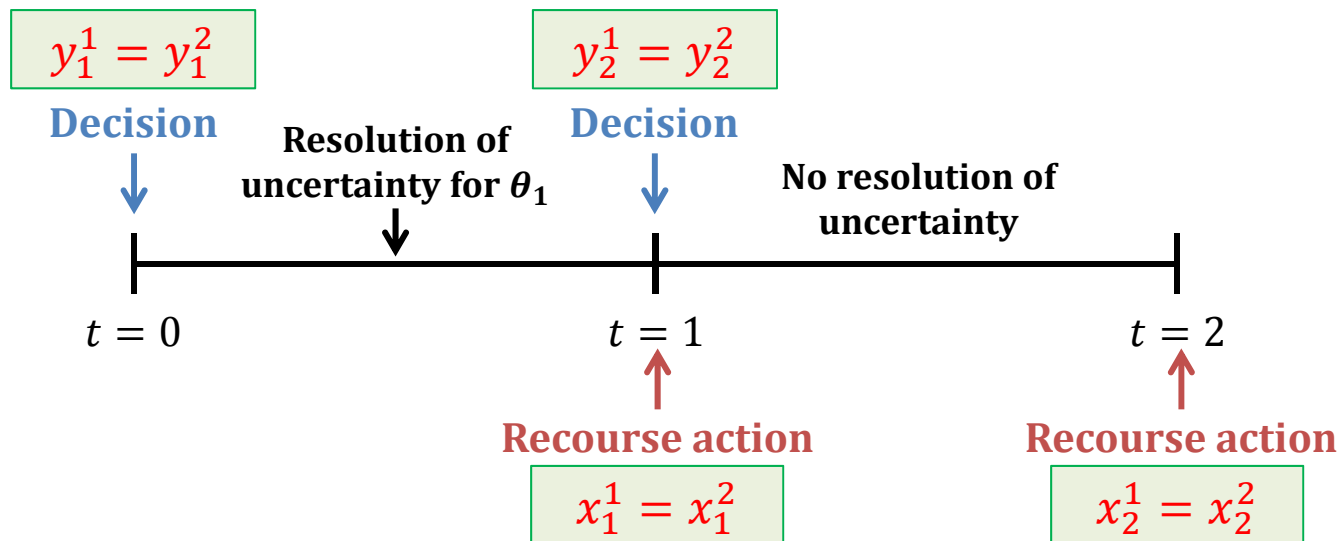
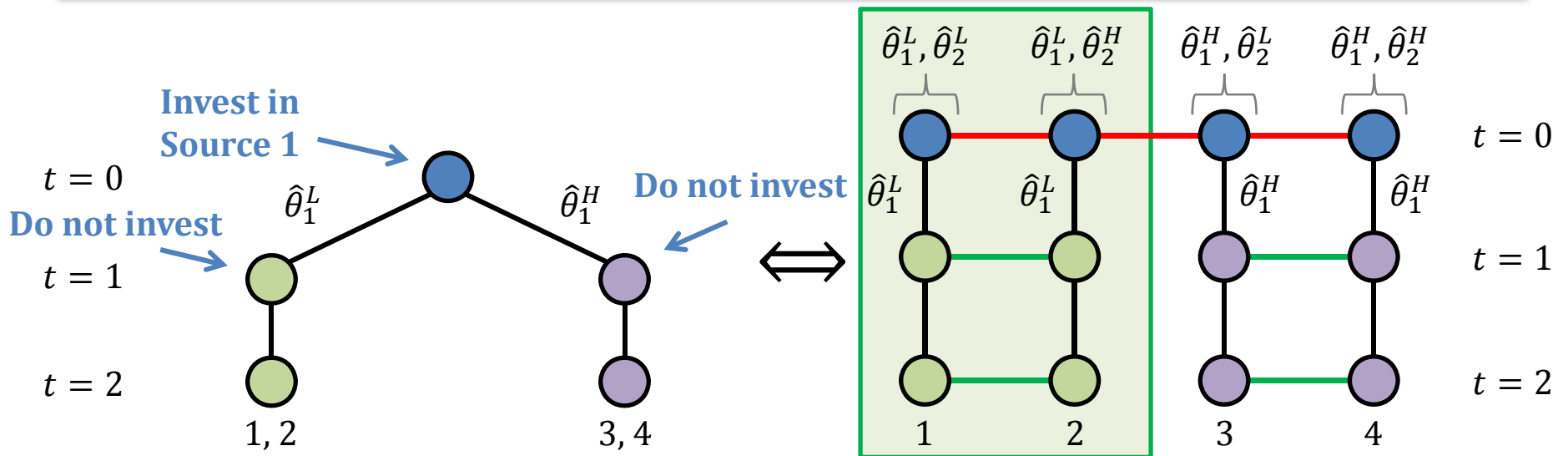


- Alternative form of tree gives each scenario a **unique set of nodes**
- Scenarios with the same information at time  $t$  are said to be **indistinguishable** at that time
- We must **make the same decisions in indistinguishable scenarios**
  - ☐ Enforced by **non-anticipativity constraints**

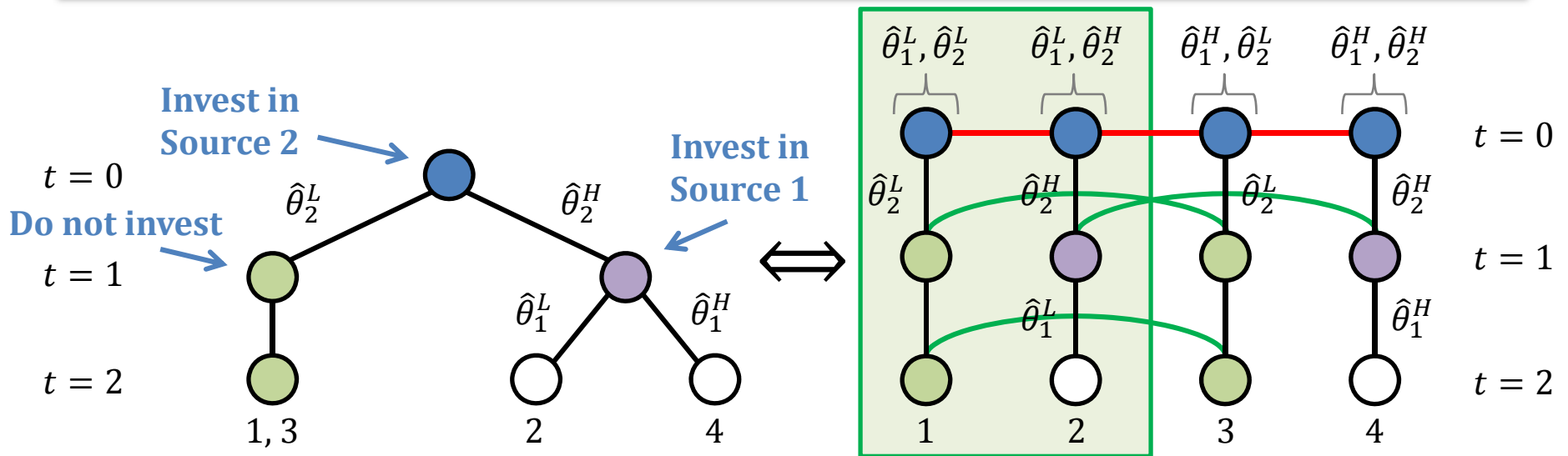
# MSSP under Exogenous Uncertainty



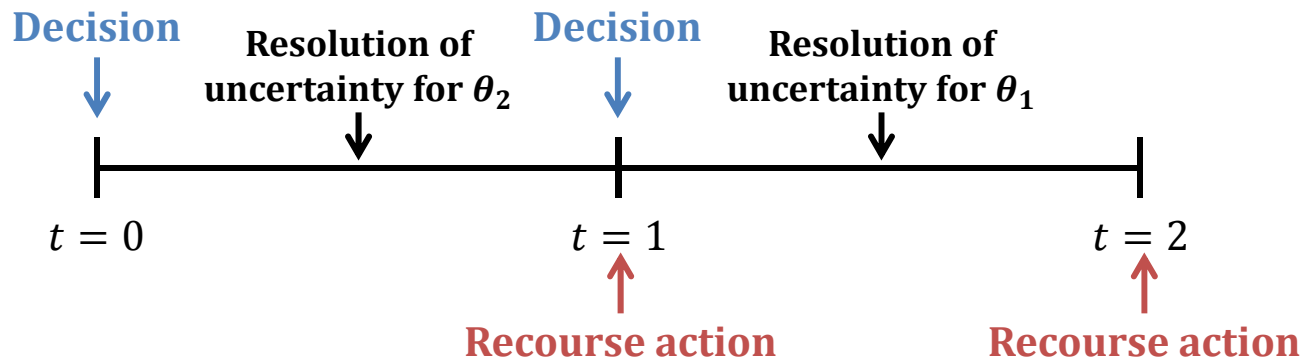
# MSSP under Endogenous Uncertainty



# MSSP under Endogenous Uncertainty



$$y_1^1 = y_1^2$$

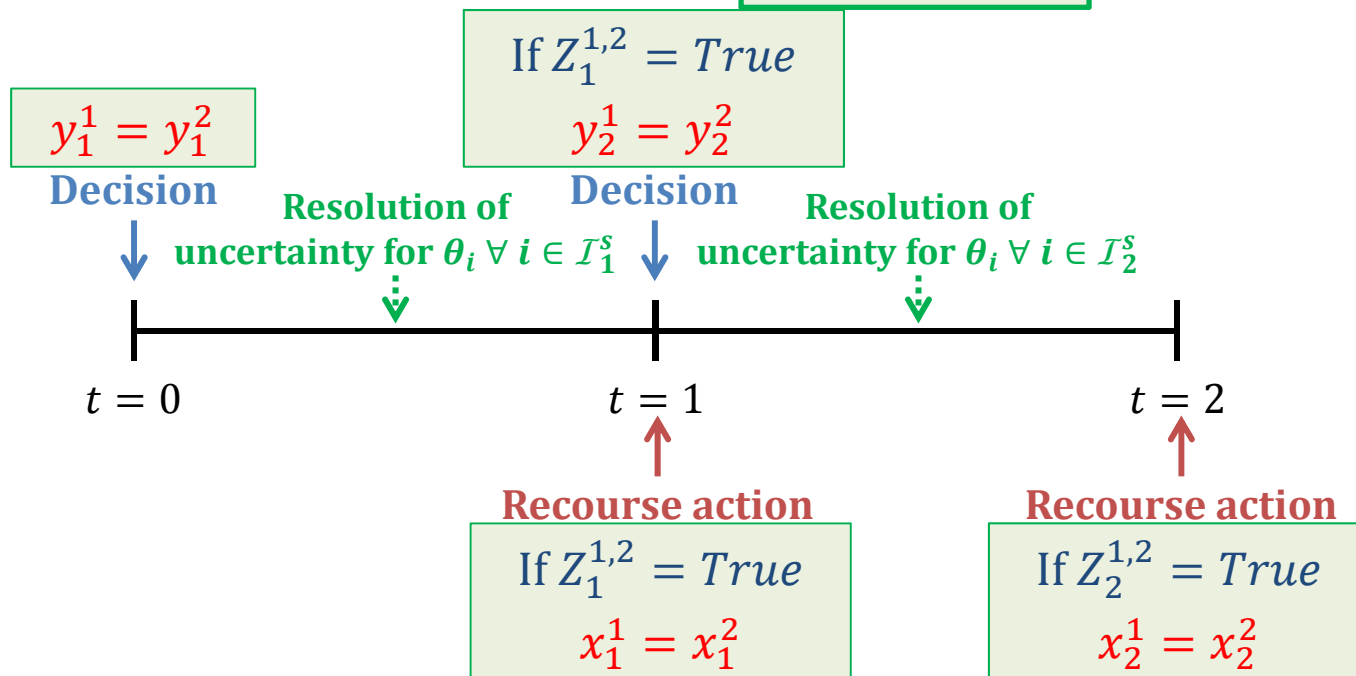
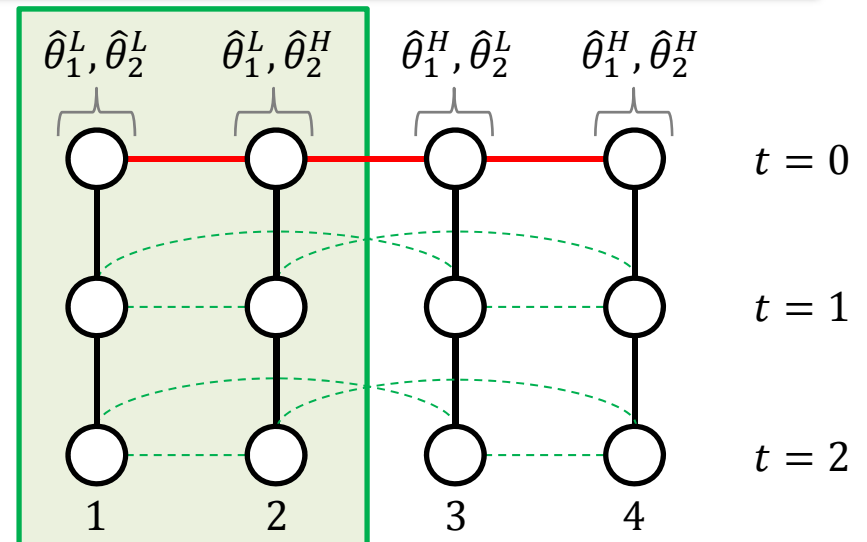




# MSSP under Endogenous Uncertainty

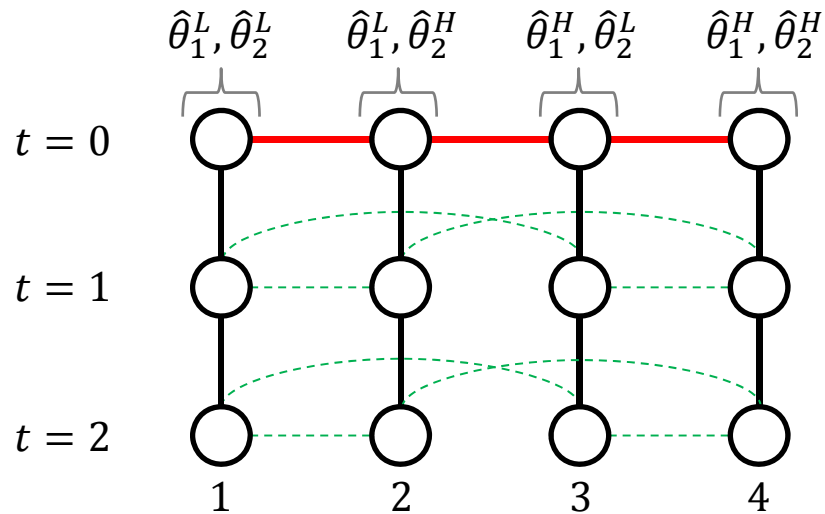
$$\begin{bmatrix} Z_t^{s,s'} \\ x_t^s = x_t^{s'} \\ y_{t+1}^s = y_{t+1}^{s'} \end{bmatrix} \vee [\neg Z_t^{s,s'}]$$

$Z_t^{s,s'} = \text{True}$  if  $(s, s')$  indistinguishable



# Description of Endogenous & Exogenous Uncertainty

## Endogenous

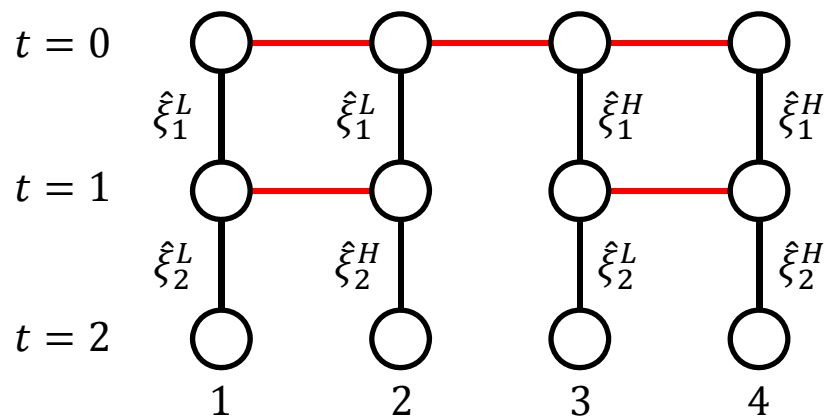


$$\begin{aligned} \mathcal{R}_N &:= \times_{i \in \mathcal{J}} \times_{h \in \mathcal{H}_i} \Theta_{i,h} \\ &= \left\{ \left( \hat{\theta}_{1,1}^1, \dots, \hat{\theta}_{I,H_I}^1 \right), \dots, \left( \hat{\theta}_{1,1}^{|\Theta_{1,1}|}, \dots, \hat{\theta}_{I,H_I}^{|\Theta_{I,H_I}|} \right) \right\} \end{aligned}$$

$$|\mathcal{R}_N| = \prod_{i \in \mathcal{J}} \prod_{h \in \mathcal{H}_i} |\Theta_{i,h}|$$

$$\mathcal{S}_N = \{1, 2, \dots, |\mathcal{R}_N|\}$$

## Exogenous



$$\begin{aligned} \mathcal{R}_X &:= \times_{t \in \mathcal{T}} \times_{j \in \mathcal{J}} \Xi_{j,t} \\ &= \left\{ \left( \hat{\xi}_{1,1}^1, \dots, \hat{\xi}_{J,T}^1 \right), \dots, \left( \hat{\xi}_{1,1}^{|\Xi_{1,1}|}, \dots, \hat{\xi}_{J,T}^{|\Xi_{J,T}|} \right) \right\} \end{aligned}$$

$$|\mathcal{R}_X| = \prod_{t \in \mathcal{T}} \prod_{j \in \mathcal{J}} |\Xi_{j,t}|$$

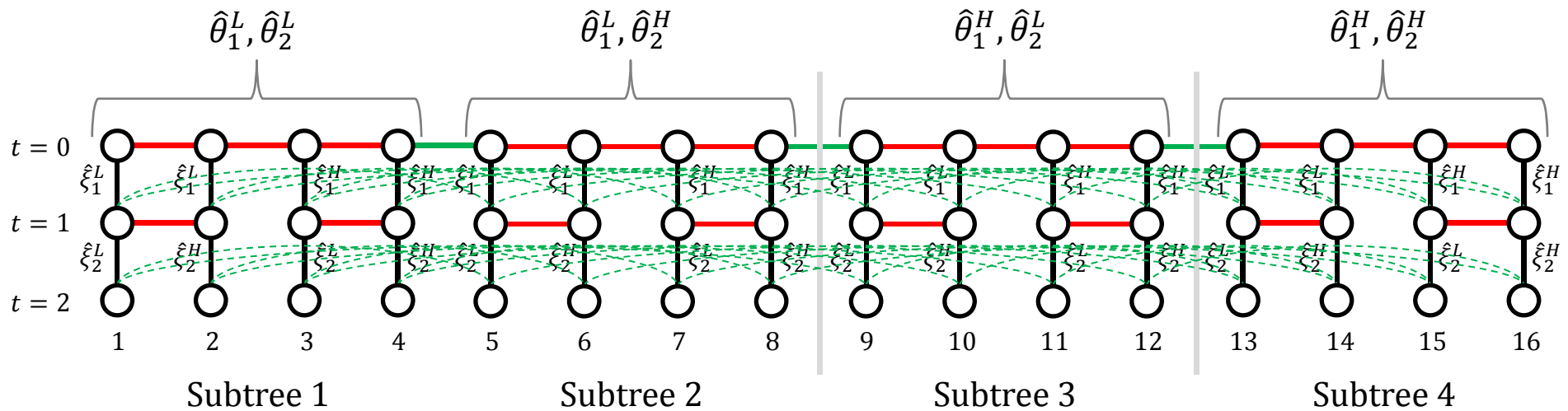
$$\mathcal{S}_X = \{1, 2, \dots, |\mathcal{R}_X|\}$$

# Description of Endogenous & Exogenous Uncertainty

## Endogenous and Exogenous

$$\mathcal{R} := \mathcal{R}_N \times \mathcal{R}_X = \left\{ \begin{array}{l} (\hat{\theta}_{1,1}^1, \dots, \hat{\theta}_{I,H_I}^1, \hat{\xi}_{1,1}^1, \dots, \hat{\xi}_{J,T}^1), \dots, (\hat{\theta}_{1,1}^1, \dots, \hat{\theta}_{I,H_I}^1, \hat{\xi}_{1,1}^{|\Xi_{1,1}|}, \dots, \hat{\xi}_{J,T}^{|\Xi_{J,T}|}), \dots, \\ \left( \hat{\theta}_{1,1}^{|\Theta_{1,1}|}, \dots, \hat{\theta}_{I,H_I}^{|\Theta_{I,H_I}|}, \hat{\xi}_{1,1}^1, \dots, \hat{\xi}_{J,T}^1 \right), \dots, \left( \hat{\theta}_{1,1}^{|\Theta_{1,1}|}, \dots, \hat{\theta}_{I,H_I}^{|\Theta_{I,H_I}|}, \hat{\xi}_{1,1}^{|\Xi_{1,1}|}, \dots, \hat{\xi}_{J,T}^{|\Xi_{J,T}|} \right) \end{array} \right\}$$

$$\mathcal{S} = \{1, 2, \dots, |\mathcal{R}|\}$$



Complete 'composite' scenario tree

# MSSP Formulation: Endogenous & Exogenous

$$\min_{b,y,x} \phi = \sum_{s \in \mathcal{S}} p^s \sum_{t \in \mathcal{T}} \left( y_{c_t^s}^s y_t^s + x_{c_t^s}^s x_t^s + w_{c_t^s}^s w_t^s + \sum_{i \in \mathcal{I}} b_{c_{i,t}^s}^s b_{i,t}^s \right)$$

**Objective function**  
(minimize expected cost)

$$\text{s.t.} \quad \sum_{\tau=1}^t \left( y_{A_{\tau,t}^s}^s y_{\tau}^s + x_{A_{\tau,t}^s}^s x_{\tau}^s + w_{A_{\tau,t}^s}^s w_{\tau}^s + \sum_{i \in \mathcal{I}} b_{A_{i,\tau,t}^s}^s b_{i,\tau}^s \right) \leq a_t^s \quad \forall t \in \mathcal{T}, s \in \mathcal{S}$$

**Decision-governing & period-linking constraints**

$$\begin{aligned} b_{i,1}^s &= b_{i,1}^{s'} & \forall (s, s') \in \mathcal{SP}_F, i \in \mathcal{I} \\ y_1^s &= y_1^{s'} & \forall (s, s') \in \mathcal{SP}_F \end{aligned}$$

**First-period NACs**

$$\begin{aligned} x_t^s &= x_t^{s'} & \forall (t, s, s') \in \mathcal{SP}_X \\ b_{i,t+1}^s &= b_{i,t+1}^{s'} & \forall (t, s, s') \in \mathcal{SP}_X, i \in \mathcal{I} \\ y_{t+1}^s &= y_{t+1}^{s'} & \forall (t, s, s') \in \mathcal{SP}_X \end{aligned}$$

**Exogenous NACs**

$$\begin{aligned} x_t^s &= x_t^{s'} & \forall (t, s, s') \in \mathcal{SP}_N, t \in \mathcal{T}_E \\ b_{i,t+1}^s &= b_{i,t+1}^{s'} & \forall (t, s, s') \in \mathcal{SP}_N, t \in \mathcal{T}_E, i \in \mathcal{I} \\ y_{t+1}^s &= y_{t+1}^{s'} & \forall (t, s, s') \in \mathcal{SP}_N, t \in \mathcal{T}_E \end{aligned}$$

**Fixed endogenous NACs**

$$\begin{aligned} -x_t^{UB} (1 - z_t^{s,s'}) &\leq x_t^s - x_t^{s'} \leq x_t^{UB} (1 - z_t^{s,s'}) & \forall (t, s, s') \in \mathcal{SP}_N, t \in \mathcal{T}_C \\ -(1 - z_t^{s,s'}) &\leq b_{i,t+1}^s - b_{i,t+1}^{s'} \leq (1 - z_t^{s,s'}) & \forall (t, s, s') \in \mathcal{SP}_N, t \in \mathcal{T}_C, t < T, i \in \mathcal{I} \\ -y_{t+1}^{UB} (1 - z_t^{s,s'}) &\leq y_{t+1}^s - y_{t+1}^{s'} \leq y_{t+1}^{UB} (1 - z_t^{s,s'}) & \forall (t, s, s') \in \mathcal{SP}_N, t \in \mathcal{T}_C, t < T \end{aligned}$$

**Conditional endogenous NACs**

$$z_t^{s,s'} \Leftrightarrow F(b_{i,1}^s, b_{i,2}^s, \dots, b_{i,t}^s) \quad \forall (t, s, s') \in \mathcal{SP}_N, t \in \mathcal{T}_C, \{i\} = \mathcal{D}^{s,s'}$$

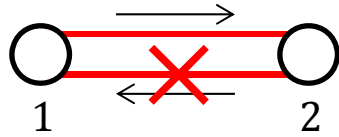
**Endogenous indistinguishability constraints**

$$\begin{aligned} b_{i,t}^s &\in \{0,1\}, y_t^s \in \mathcal{Y}_t^s, x_t^s \in \mathcal{X}_t^s, w_t^s \in \mathcal{W}_t^s & \forall i \in \mathcal{I}, t \in \mathcal{T}, s \in \mathcal{S} \\ z_t^{s,s'} &\in \{True, False\}, z_t^{s,s'} \in \{0,1\} & \forall (t, s, s') \in \mathcal{SP}_N, t \in \mathcal{T}_C \end{aligned}$$

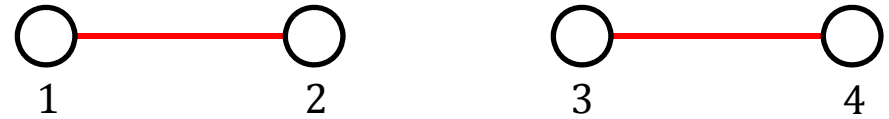
**Bounds & integrality restrictions**

# Eliminating Redundant NACs

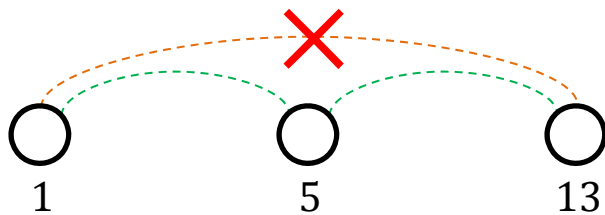
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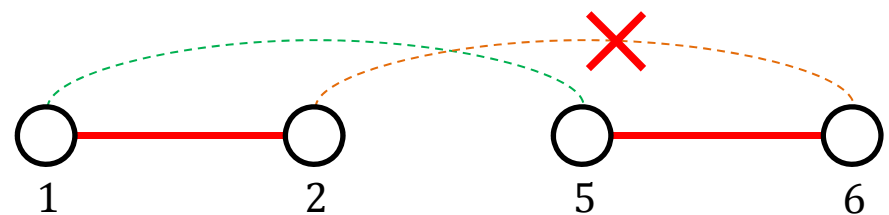
**Symmetry**  
*Property 1*



**Adjacency**  
*Properties 2a & 2b*



**Transitivity**  
*Properties 3 & 4*



**Grouping**  
*Property 5*

- Even after eliminating redundant constraints, **models are typically still too large** to be solved directly
- We consider **special solution methods**:
  - Sequential scenario decomposition (SSD) heuristic
  - Lagrangean decomposition (LD)

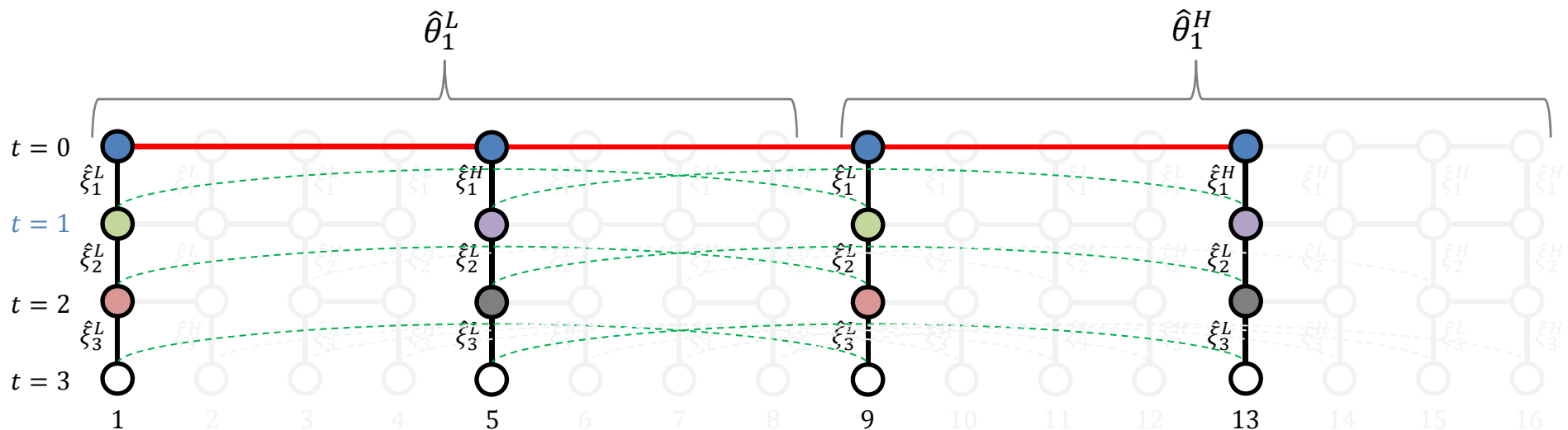
# Solution Method 1: SSD Heuristic

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- Basic idea behind **sequential scenario decomposition (SSD)**:
  - ❑ Select a **subset of scenarios** in each time period
  - ❑ Solve an **MILP subproblem** involving only those scenarios for the full time horizon
  - ❑ **Take binary decisions** from the subproblem solution
  - ❑ **Fix these binary decisions** in scenarios of the original problem to satisfy first-period and exogenous NACs
  - ❑ Proceed to next time period and **repeat**
  - ❑ **Solve the resulting model** to obtain a feasible solution to the original problem

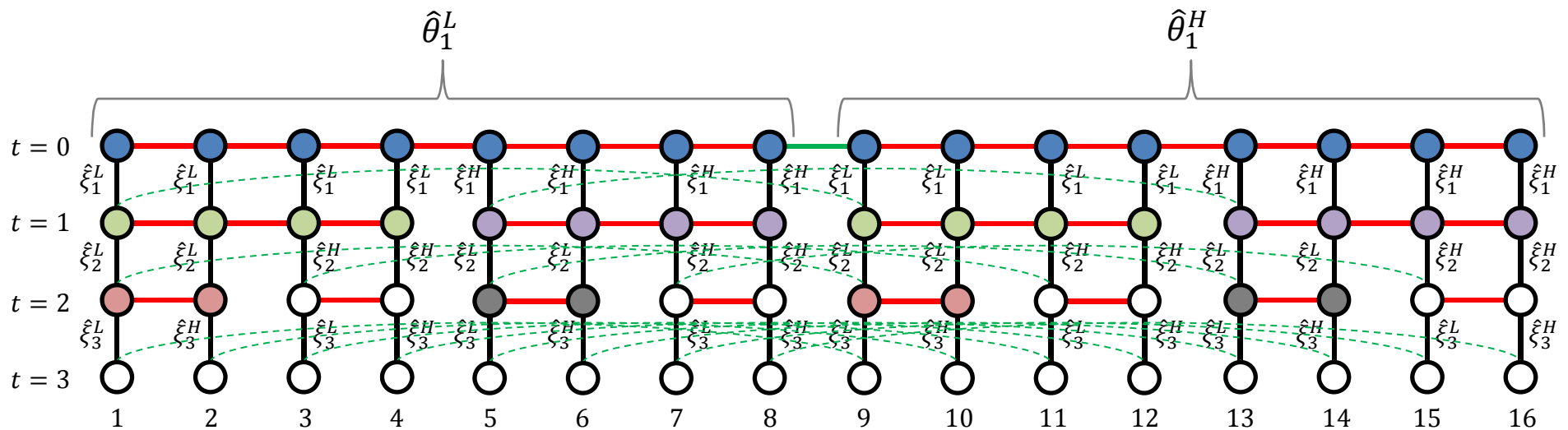
# Solution Method 1: SSD Heuristic

- **Solve an MILP subproblem** that consists of only the selected scenarios **{1, 5, 9, 13}**
- This subproblem includes first-period NACs and endogenous NACs, but **no exogenous NACs**



# Solution Method 1: SSD Heuristic

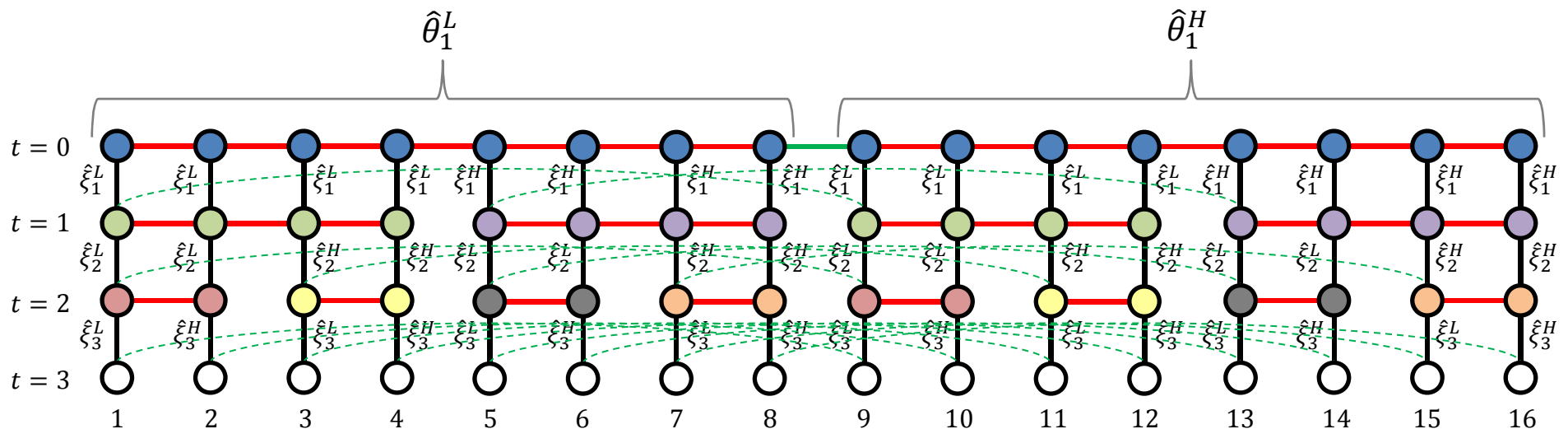
- Extract binary investment decisions from solution, and fix in corresponding scenario groups to satisfy first-period and exogenous NACs





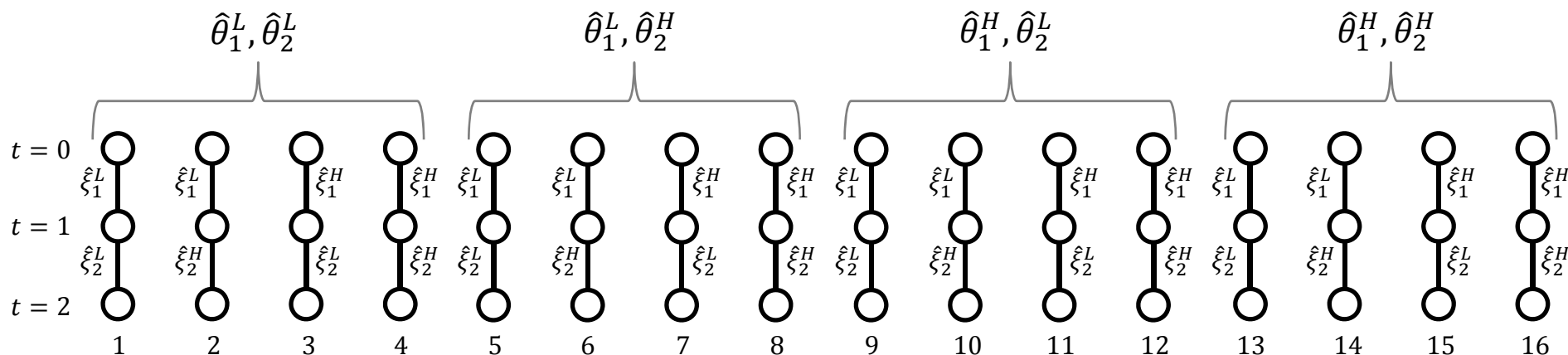
# Solution Method 1: SSD Heuristic

- After repeating procedure for each subproblem, **all binary variables are fixed**. Thus, the scenario tree is fixed
- The solution of the resulting problem is a **feasible (but not necessarily optimal) solution** to the original MILP



# Solution Method 2: Lagrangean Decomposition

- If non-anticipativity constraints are removed, the scenario tree decomposes into independent scenarios
- Set up **Lagrangean dual problem**:
  - ❑ Relax **conditional endogenous** NACs
  - ❑ Dualize **first-period** and **exogenous** NACs



# Solution Method 2: Lagrangean Decomposition

$$\min_y \phi = \sum_{s \in \mathcal{S}} p^s \sum_{t \in \mathcal{T}} y^s c_t^s y_t^s$$

$$\text{s.t.} \quad \sum_{\tau=1}^t y^s A_{\tau,t}^s y_{\tau}^s \leq a_t^s \quad \forall t \in \mathcal{T}, s \in \mathcal{S}$$



$$y_1^s = y_1^{s'} \quad \forall (s, s') \in \mathcal{SP}_F$$

$$y_{t+1}^s = y_{t+1}^{s'} \quad \forall (t, s, s') \in \mathcal{SP}_X$$

$$y_{t+1}^s = y_{t+1}^{s'} \quad \forall (t, s, s') \in \mathcal{SP}_N, t \in \mathcal{T}_E$$

~~$$-y_{t+1}^{s'} (1 - z_t^{s,s'}) \leq y_{t+1}^s - y_{t+1}^{s'} \leq y_{t+1}^{UB} (1 - z_t^{s,s'}) \quad \forall (t, s, s') \in \mathcal{SP}_N, t \in \mathcal{T}_C, t < T$$~~

~~$$z_t^{s,s'} \in F(y_1^s, y_2^s, \dots, y_t^s) \quad \forall (t, s, s') \in \mathcal{SP}_N, t \in \mathcal{T}_C$$~~

$$y_t^s \in \mathcal{Y}_t^s \quad \forall t \in \mathcal{T}, s \in \mathcal{S}$$

~~$$z_t^{s,s'} \in \{\text{True}, \text{false}\}, z_t^{s,s'} \in \{0, 1\} \quad \forall (t, s, s') \in \mathcal{SP}_N, t \in \mathcal{T}_C$$~~

# Solution Method 2: Lagrangean Decomposition

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$$\min_y \phi_{LD} = \sum_{s \in \mathcal{S}} p^s \sum_{t \in \mathcal{T}} \left( y^s c_t^s y_t^s + y_1^s \left( \sum_{(s,s') \in \mathcal{SP}_F} F \lambda_1^{s,s'} - \sum_{(s',s) \in \mathcal{SP}_F} F \lambda_1^{s',s} \right) + y_{t+1}^s \left( \sum_{(t,s,s') \in \mathcal{SP}_X} X \lambda_t^{s,s'} - \sum_{(t,s',s) \in \mathcal{SP}_X} X \lambda_t^{s',s} \right) + y_{t+1}^s \left( \sum_{\substack{(t,s,s') \in \mathcal{SP}_N \\ t \in \mathcal{T}_E}} N \lambda_t^{s,s'} - \sum_{\substack{(t,s',s) \in \mathcal{SP}_N \\ t \in \mathcal{T}_E}} N \lambda_t^{s',s} \right) \right)$$

$$\text{s. t. } \sum_{\tau=1}^t y^s A_{\tau,t}^s y_{\tau}^s \leq a_t^s \quad \forall t \in \mathcal{T}, s \in \mathcal{S}$$

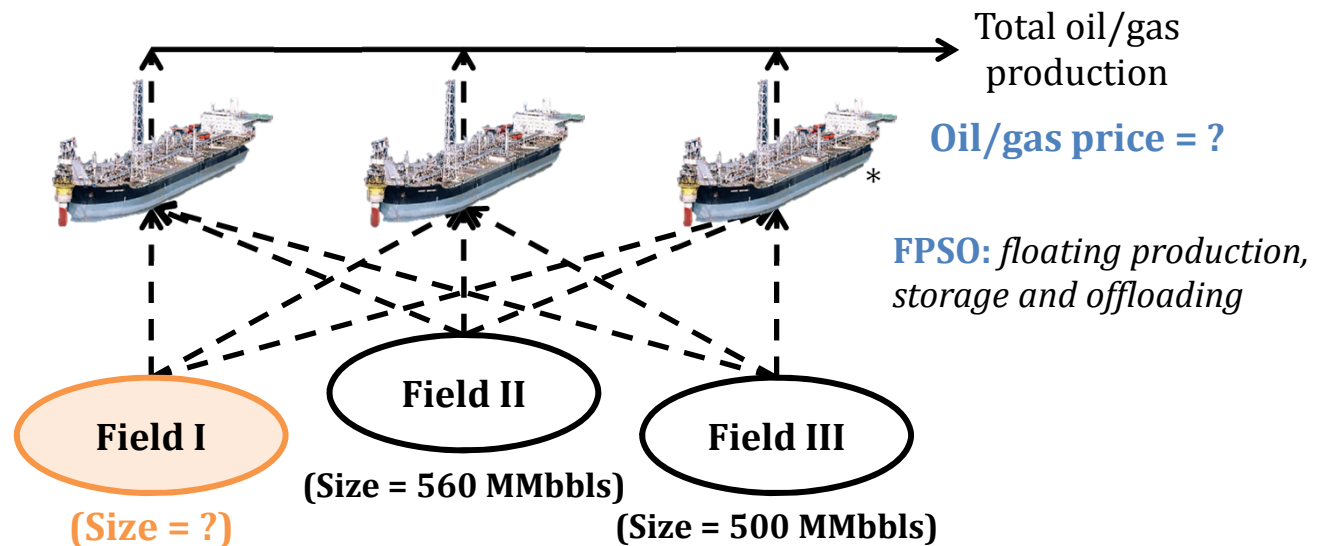
$$y_t^s \in \mathcal{Y}_t^s \quad \forall t \in \mathcal{T}, s \in \mathcal{S}$$

✓ **Lagrangean relaxation**

✓ **Decompose problem by scenario**

- ❑ Solve scenario subproblems in parallel
- ❑ Update multipliers using subgradient method

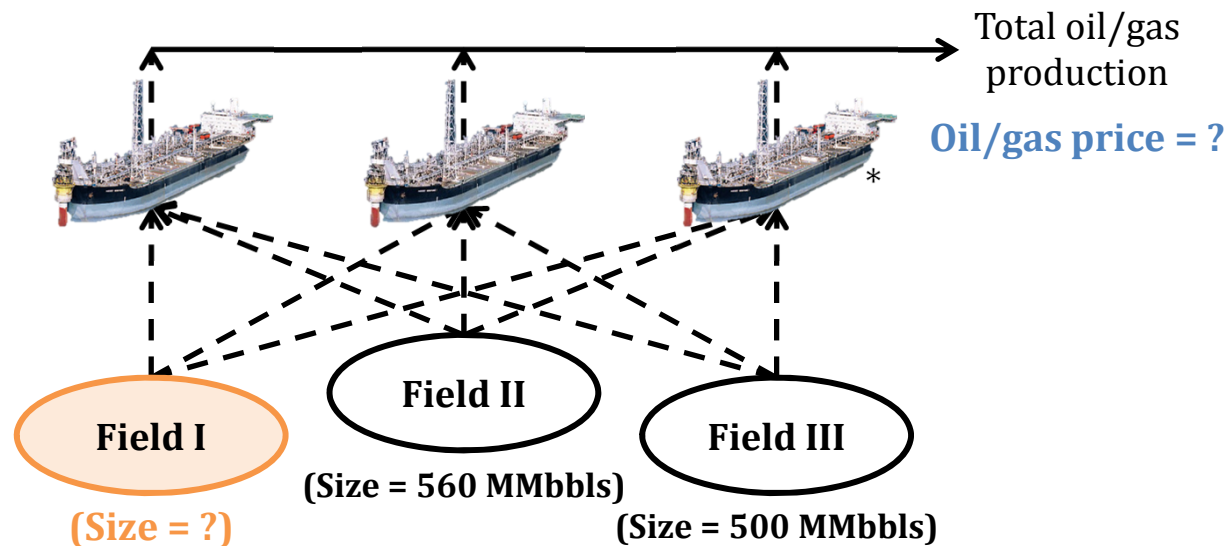
# Example: Oilfield Development Planning



- Planning over **5 years**
- Determine **optimal investment and operations decisions**
- **Here-and-now decisions:** FPSO installations and expansions, field-FPSO connections (9 possible), well-drilling schedule (30 potential wells)
- **Recourse decisions:** Oil production rate

**Objective: Maximize total expected NPV**

# Example: Oilfield Development Planning



(2 realizations for size)<sup>(1 uncertain size)</sup>



**2 endogenous combinations**

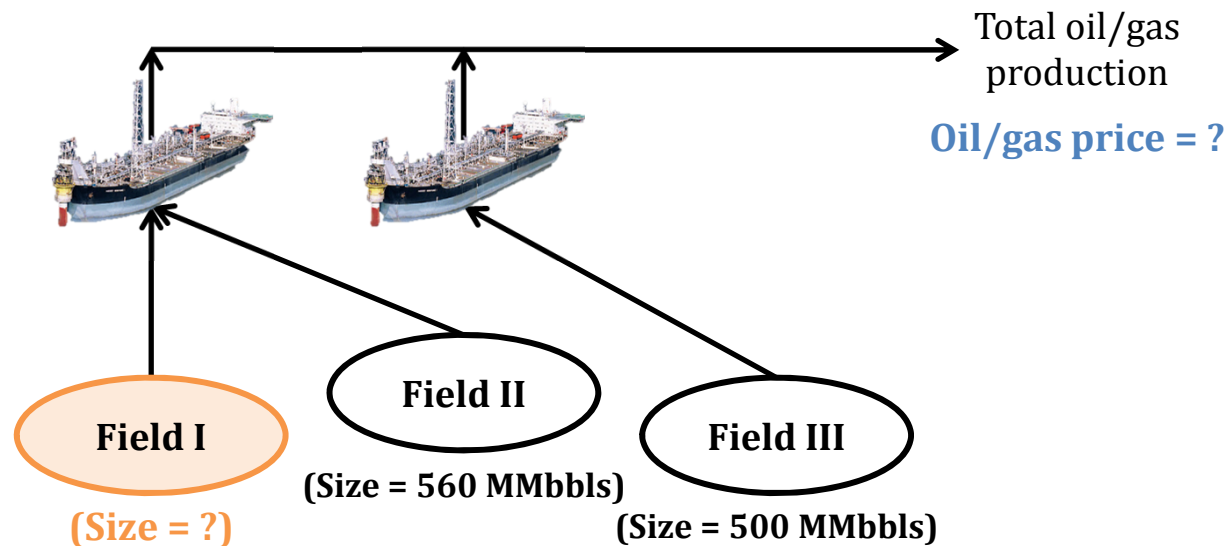
(2 realizations for price)<sup>(5 time periods)</sup>



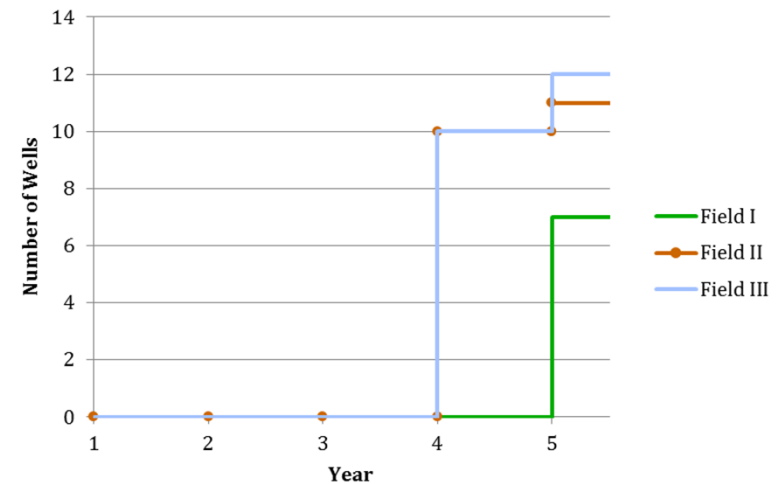
**32 exogenous combinations**

**(2 endogenous combinations) × (32 exogenous combinations)  $\Rightarrow$  64 scenarios**

# Example: Oilfield Development Planning



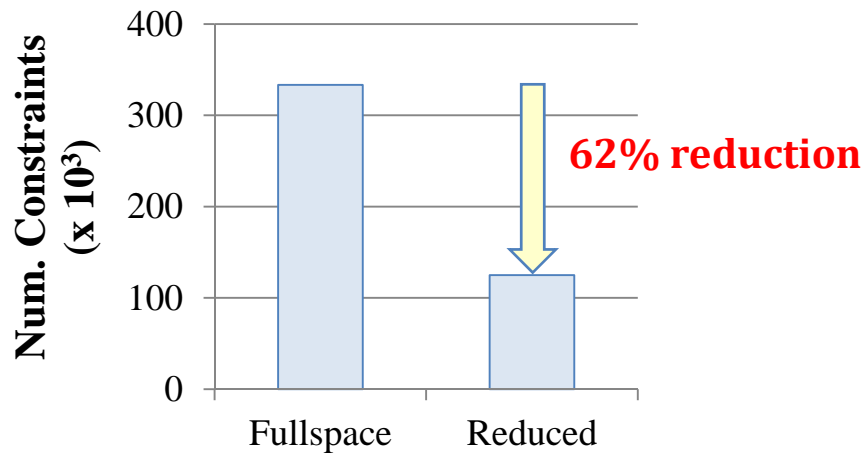
- **Begin installing all infrastructure in first year**
- **Drilling cannot start until year 4**  
due to lead time for FPSO installation
- **Drill fields with known size first**



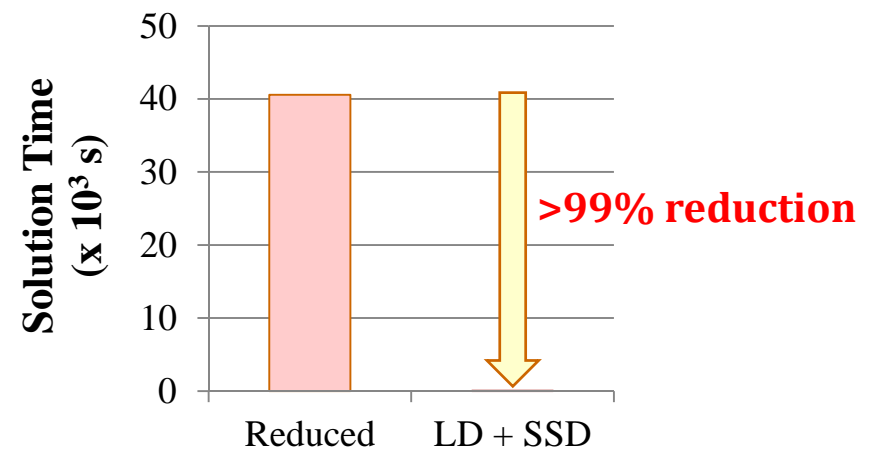
# Example: Oilfield Development Planning

| Problem Type  | Total Expected NPV (\$B) |             | Optimality Gap | Number of Constraints | Continuous Variables | 0, 1 Variables     | Solution Time (s) |
|---------------|--------------------------|-------------|----------------|-----------------------|----------------------|--------------------|-------------------|
|               | Lower Bound              | Upper Bound |                |                       |                      |                    |                   |
| Fullspace     | -                        | -           | -              | 333,249               | 70,465               | 7,360              | -                 |
| Reduced Model | 6.968                    | 10.495      | 50.61%         | 124,980               | 70,465               | 7,000              | 40,562            |
| SSD           | 7.166                    | -           | 0.20%          | 28,687 <sup>1</sup>   | 17,329 <sup>1</sup>  | 1,224 <sup>1</sup> | 41                |
| LD            | -                        | 7.180       |                | 3,776                 | 2,203                | 218                | 14                |

<sup>1</sup> Largest subproblem



Comparison of Instance Sizes



Comparison of Solution Methods



# Conclusions

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- Multistage stochastic optimization problems often contain **both endogenous and exogenous** uncertain parameters
- We have presented a '**composite**' **scenario tree** that captures endogenous and exogenous realizations
- We have proposed a **reduced model** for **MSSP under both types of uncertainty** by eliminating redundant NACs based on the structure of the underlying scenario tree
- To demonstrate practical solution methods for this class of problems, we have applied **Lagrangian decomposition** and a novel **sequential scenario decomposition heuristic** to an example problem
  - ❑ Both alternative methods are considerably faster than solving the reduced model directly

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