Hierarchical TSO-DSO Coordination

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Outline

- Motivation
- Optimization Policies
- Two-Layer model
- Multi-Layer model

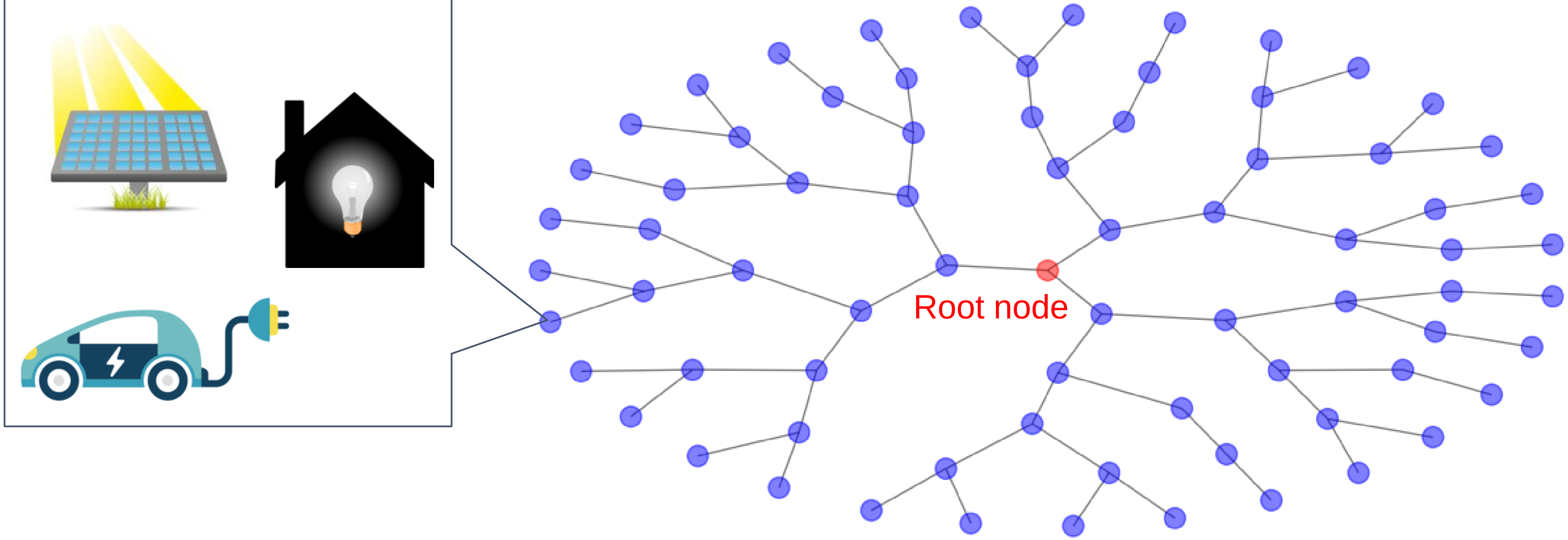
Motivation

Motivation

- A recent study by Imperial College estimates the value of mobilizing flexibility at **8 billion British pounds per year** for the UK alone
- A good part of this flexibility is located in distribution systems
- Challenges of distribution system coordination
  - Scale
  - Non-linearity of power flow
  - Uncertainty
- This work proposes a hierarchical approach towards tackling these challenges

Flexible Resources in Distribution Systems

Goal: dispatch the system at minimum cost



Optimization Policies

Policies

1. Model Predictive Control (MPC)
    a. Certainty-Equivalent MPC
    b. Scenario-Based Robust MPC
2. Stochastic Dual Dynamic Programming (SDDP)
3. Our contribution: **Decomposed SDDP**

Model Predictive Control

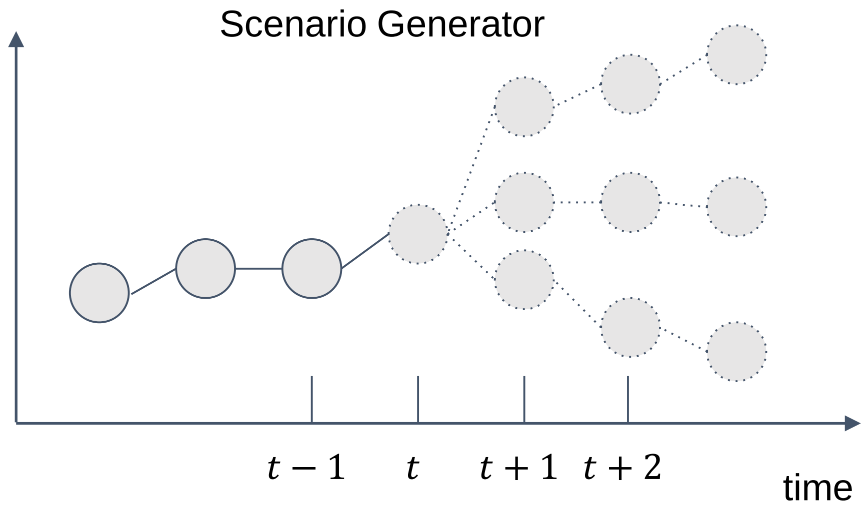
- At each time step t,
    - **Predict**: predict the uncertainty (e.g. production of PV power) for $t, t + 1, \dots, H$ to construct a look-ahead optimization problem
    - **Optimize**: optimize the problem over $t, \dots, H$ and obtain the optimal solution x^*
    - **Execute**: carry out the solution of time t, x_t^*

- E.g. certainty-equivalent MPC (**ceMPC**)
    - Replace the uncertainty by the **expected value**
    - Light computation, useful for *online* applications

Scenario-Based Robust MPC (sbrMPC)

For every time step (**online**)

- Generate $1, \ldots, S$ scenarios by a scenario generator
- Minimize the cost of the **worst-case** scenario



Pros:
- ❖ Simple to model
- ❖ Good performance

Cons:
- ❖ Heavy computation for online applications
  - ➢ **Not scalable**

$$\min \max_{s} \sum_{\tau=t}^{H} c_\tau^T x_\tau^{(s)}$$

s.t. $A^{(s)} x^{(s)} = b^{(s)}$

x_t equal for all s

Cost from t to $t+H$

Linear constraints for each scenario

The solution at time t must be equal for all scenarios

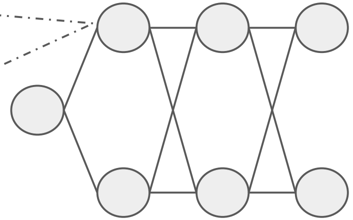
Stochastic Dual Dynamic Programming

- Solve a stochastic linear program **offline** by decomposition and Monte-Carlo simulation
  - Uncertainty is expressed in a **lattice**
  - Learn the **value function**: cost of remaining stages
- Use the value function **online** to generate a decision

$$
\begin{aligned}
NLDS_{t,k} : \min_{x}\ & c_{t,k}^T x + \boxed{V_{t,k}(x)} \\
& W_{t,k}x = h_{t,k} - T_{t,k}\hat{x}_{t-1} \\
& x \geq 0
\end{aligned}
$$

Cost from stage t + 1 to horizon H

Lattice

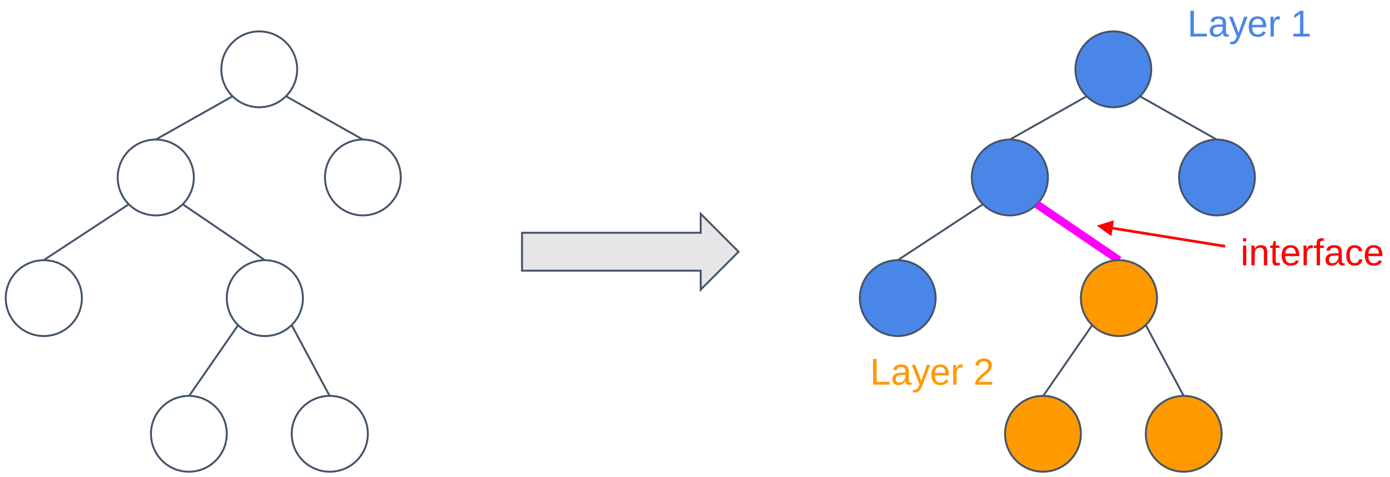


Pros:
- ❖ Provides the "optimal" solution
- ❖ Small online computation time

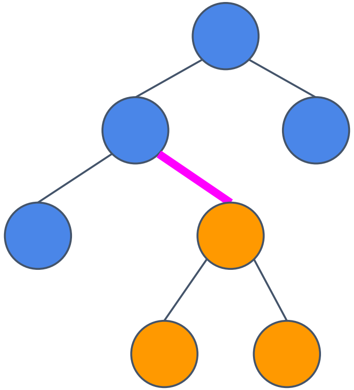
Cons:
- ❖ Size of the lattice must be "reasonable"
  - ➢ **Not scalable** to the size of network

Decomposition of a Radial Network

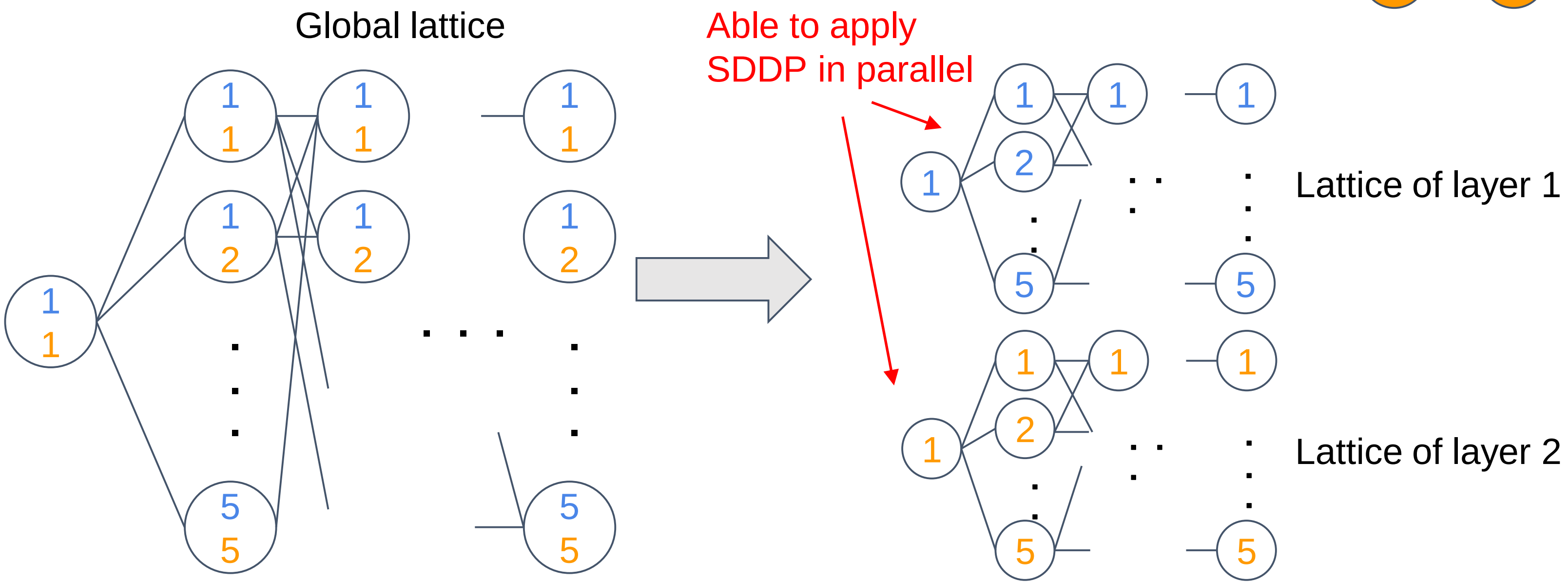
- Neither sbrMPC nor SDDP are **scalable** to the size of the network
- Our proposed hierarchical approach: decompose network by layers
  - Solve a stochastic problem at each layer independently
  - Layers communicate at the **interface**
  - **Scalable** to arbitrary size



Decomposition of Lattice



- Generate **local lattices** by decomposing the network
  - Global lattice: 5^2=25 nodes at each stage
  - Local lattice: 5 nodes at each stage

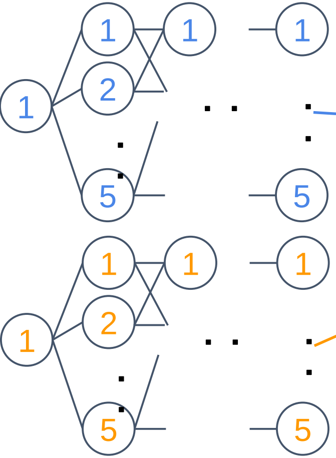


Procedure of the Decomposed SDDP Method

Offline → **Online**

Implement SDDP on each layer

➢ Obtain the value functions



V^1 Value function of layer 1

V^2 Value function of layer 2

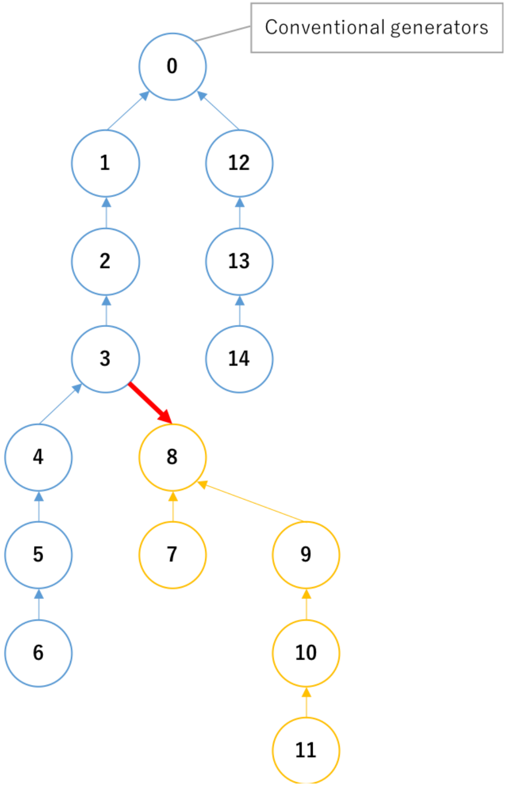
Use the value functions to solve the problem

$$\begin{aligned} \min \quad & c^T x + V^1(x^1) + V^2(x^2) \\ & Wx = h - Tx_{t-1} \\ & x \geq 0 \end{aligned}$$

Two-Layer Model

Two-Layer Model

- 15 nodes with two layers (upper and lower layer)
  - Interface is from node 3 to node 8
- Supply is only available at the root node of the upper layer (node 0)
- Stochastic parameters:
  - Net demand (= demand - PV power) at each node
  - Capacity of root supply at node 0: negatively correlated to the amount of net demand
- Lattice: 5 outcomes at each layer (globally 25 outcomes) at each stage, 24 stages



Objective and Balance: Upper Layer

$$\min \quad \sum_{g\in G} MC_g \cdot p_g + \sum_{n\in N_U} VOLL \cdot ls_n$$

Cost: fuel cost + load shedding

$$bd_n + \sum_{m\in C_n} f_m + ls_n - bc_n - ps_n - f_n = ND_n, n \in N_U \setminus \{0, n_U\}$$

Power Balance

$$\sum_{g\in G} p_g + bd_0 + \sum_{m\in C_0} f_m + ls_n 0 - bc_0 - ps_0 = ND_0$$

Power Balance at the root (only for the upper layer)

Root supply

$$s_n - \eta_n bc_n + \frac{bd_n}{\mu_n} - \hat{s}_{n,t-1} = 0, n \in N_U$$

Dynamics of storage

Storage level of the previous stage

Objective and Balance: Lower Layer

$$\min \boxed{\sum_{n \in N_L} VOLL \cdot ls_n}$$

No generator in lower layer

Cost: load shedding

$$bd_n + \sum_{m \in C_n} f_m + ls_n - bc_n - ps_n - f_n = ND_n, n \in N_L \setminus \{n_L\}$$

Power Balance

$$s_n - \eta_n bc_n + \frac{bd_n}{\mu_n} - \hat{s}_{n,t-1} = 0, n \in N_L$$

Dynamics of storage

Balance at Interface Nodes

- Upper layer

Injection to the lower layer

$$bd_{n_U} + \sum_{m \in C_{n_U} \setminus n_L} f_m + ls_{n_U} - bc_{n_U} - ps_{n_U} - f_{n_U} \boxed{- p_{\text{out}}} = ND_{n_U}$$

- Lower layer

Power flow from the upper layer

$$bd_{n_L} + \sum_{m \in C_{n_L}} f_m + ls_{n_L} - bc_{n_L} - ps_{n_L} \boxed{+ f_{n_L}} = ND_{n_L}$$

- Interface flow is **fixed** for the decomposed SDDP

$$p_{\text{out}} = \boxed{\bar{p}_{\text{out},t,k}}$$

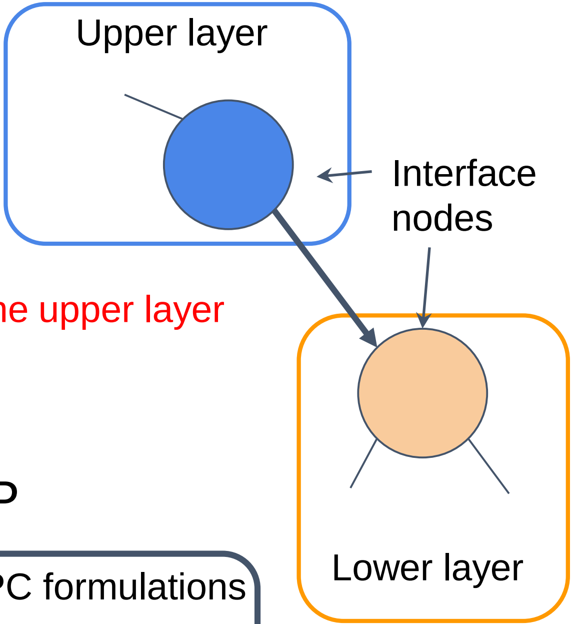
$$f_n = \boxed{\bar{f}_{n,t,k}}$$

Decided by heuristic

For full SDDP and MPC formulations

$$f_n - p_{\text{out}} = 0$$

Interface flow must be equal



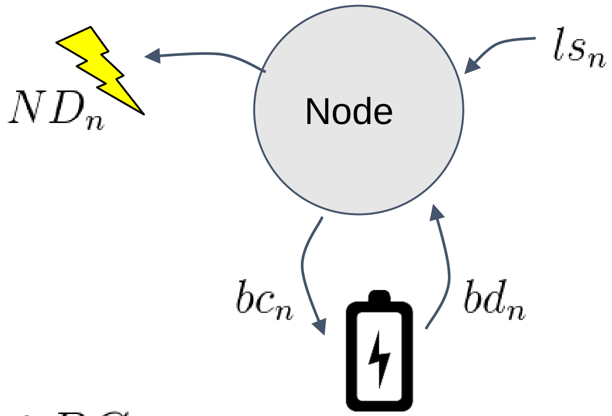
Common Constraints

- Injection limit

$$IMin_n \leq ls_n + bd_n - bc_n - ND_n \leq IMax_n$$

- Capacity constraints and non-negativity

$$PMin_g \leq p_g \leq PMax_g, 0 \leq s_n \leq S_n, 0 \leq bc_n \leq BC_n,$$
$$0 \leq bd_n \leq BD_n, -L_i \leq f_i \leq L_i$$

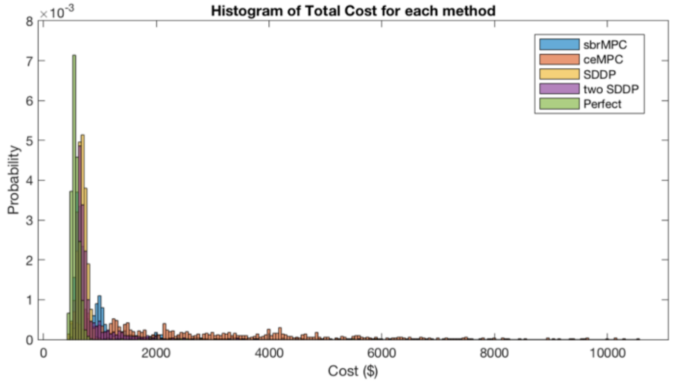


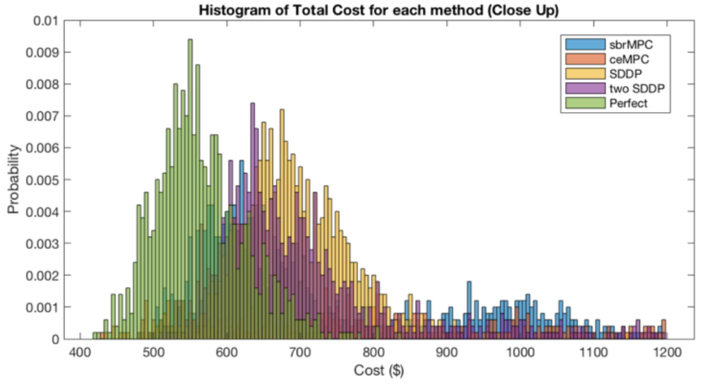
Results: Two-Layer System

- Each policy is tested against 1000 samples

	Mean ($)	SD ($)
Perfect Foresight	577	199
ceMPC	2610	2051
sbrMPC (5 scenarios)	938	688
SDDP	733	282
Decomposed SDDP	802	393

Good performance

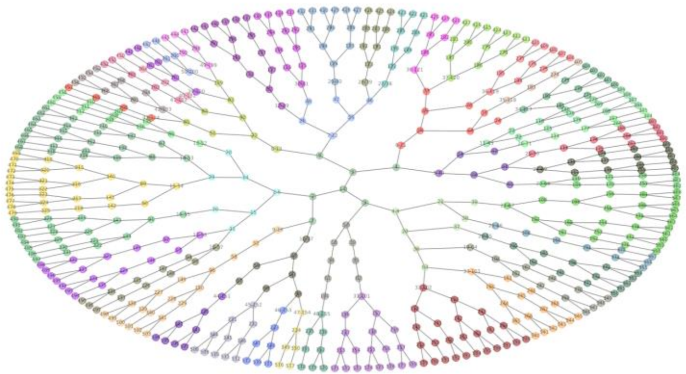




Multi-Layer Model

Multi-Layer Model

- 589 nodes with 50 layers
- Local lattice: 5 nodes with 24 stages
- Thermal generators are available at the root node
- Stochastic parameters:
    - Net demand: **spatially** and **temporally** correlated (using copula)
    - Capacity of root supply: negatively correlated to net demand
- Similar formulation as two-layer model



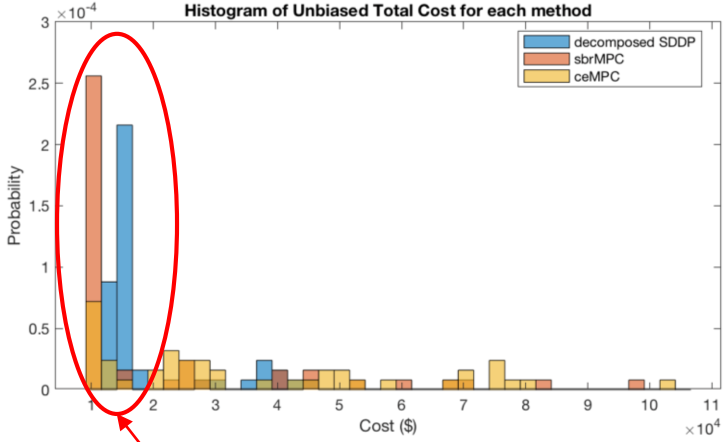
Results: Multi-Layer System

- Test each policy against 50 samples selected by importance sampling
- Each SDDP takes about 0.5h-1.5h (depends on size of the layer)

	Max online solve time (s)	Mean ($)	SD ($)
ceMPC	7.5	39299	30342
sbrMPC	754.2	23599	24930
Decomposed SDDP	5.0	19274	9444

Heavy computation

Best performance



- SDDP is risk-averse
- sbrMPC outperforms in some “easy” scenarios

Future Work

Hybrid: Decomposed SDDP + MPC

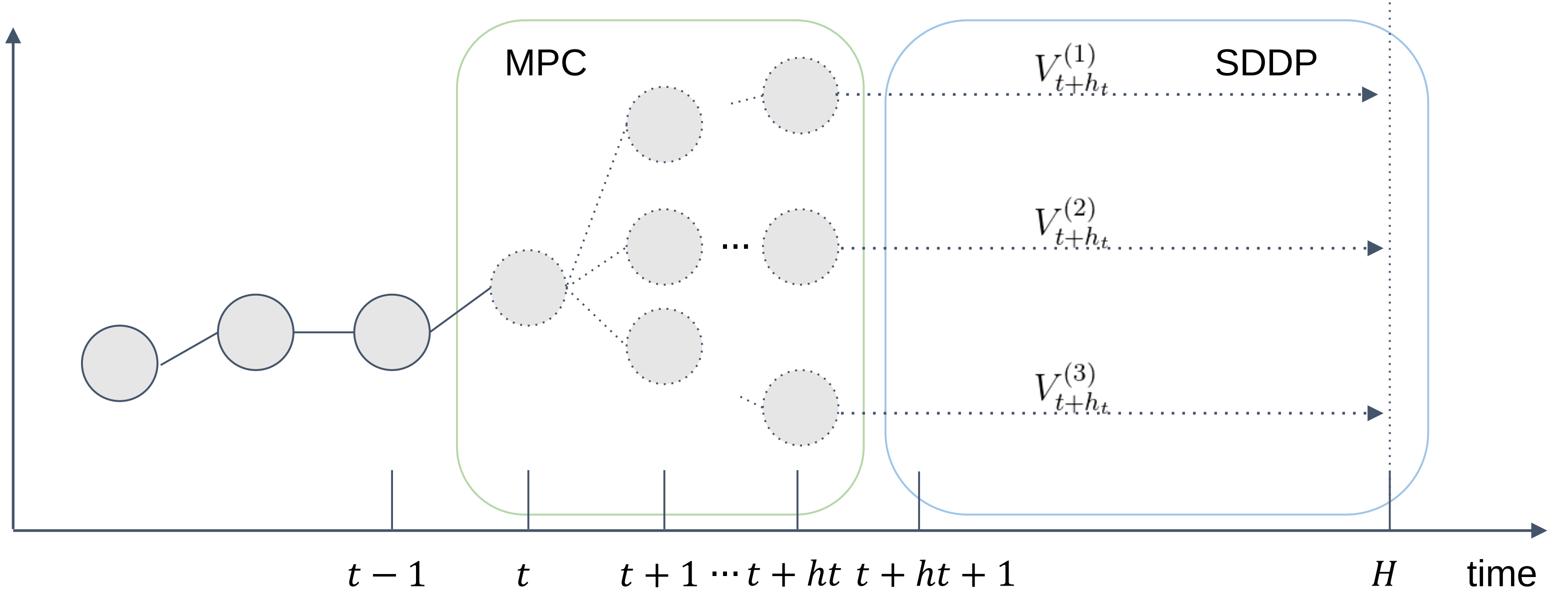
- Decomposed-SDDP
  - Value function hedges well against future risk
  - But suboptimal in some scenarios, possibly (?) due to decomposition of lattice
- sbrMPC
  - Works better in scenarios with abundant supply
  - But heavy computation is necessary (especially at early stages)

➢ Combine the two policies: sbrMPC with the value function

- ❖ Acceptable online computation time?
- ❖ Better performance than decomposed-SDDP in scenarios with abundant supply?

Hybrid: Decomposed SDDP + MPC

- sbrMPC with a limited future forecast: stage $t, \ldots, t + ht$
- Add the value function at $t + h_t$ in order to account for costs of stages $t + ht + 1, \ldots, H$



Thank you

For more information

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