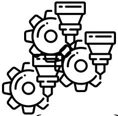
Coupled industrial production and energy supply planning
PGMO Days

Zoé Fornier
November 2022

CONTENTS

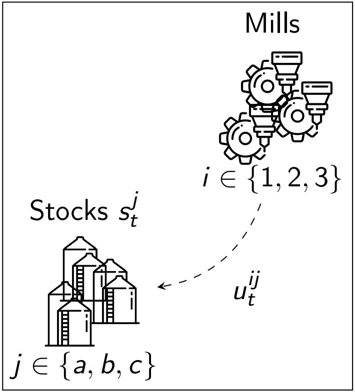
CONTEXT

Mills



$i \in \{1, 2, 3\}$

CONTEXT



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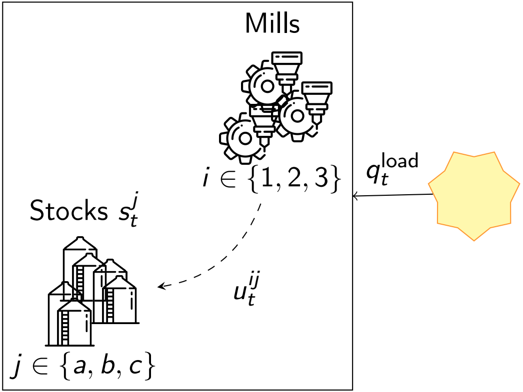

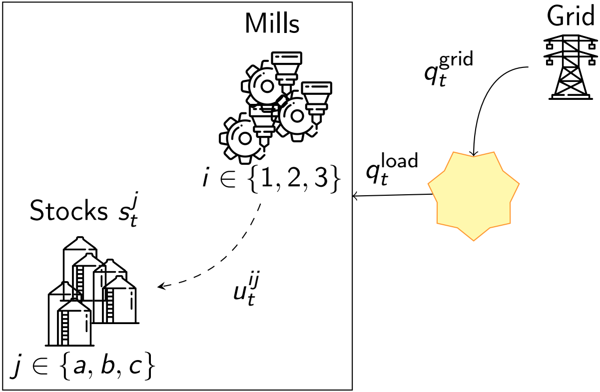
Mills
$i \in \{1, 2, 3\}$
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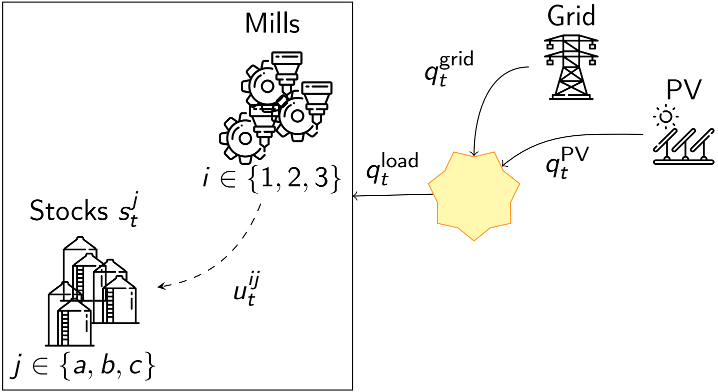
$j \in \{a, b, c\}$
u_t^{ij}
Grid
q_t^{grid}
q_t^{load}

CONTEXT



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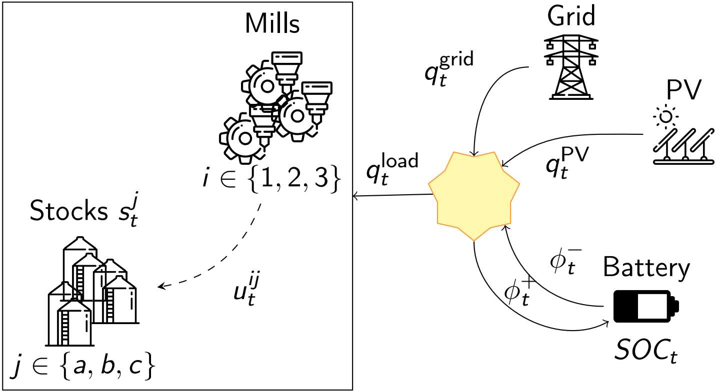
CONTEXT



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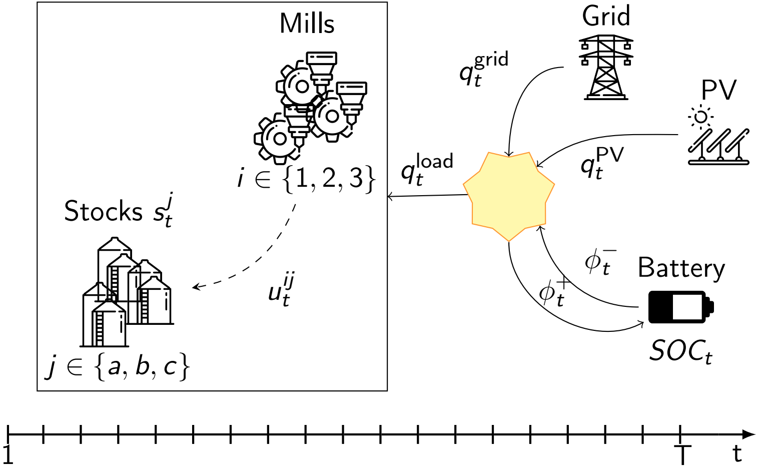
SOC_t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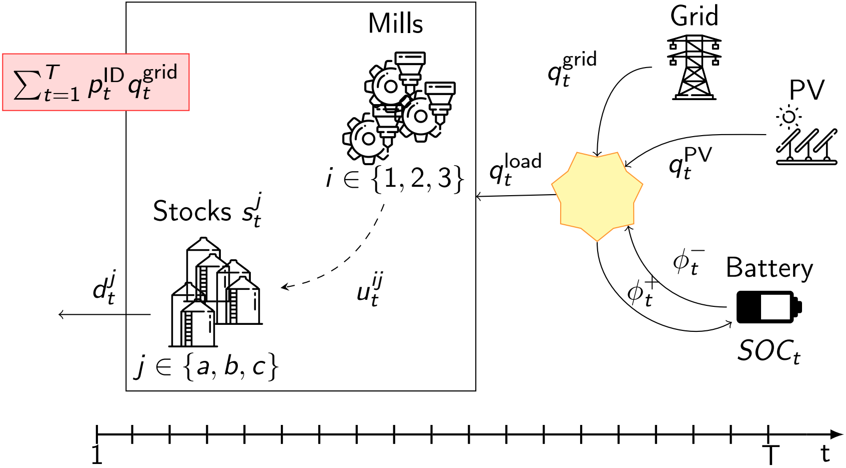
1
T
t

CONTEXT



$\sum_{t=1}^{T} p_t^{ID} q_t^{grid}$
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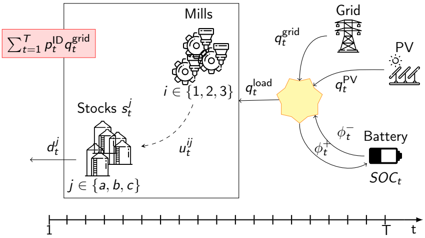
CONTEXT

Operational Problem



CONTEXT

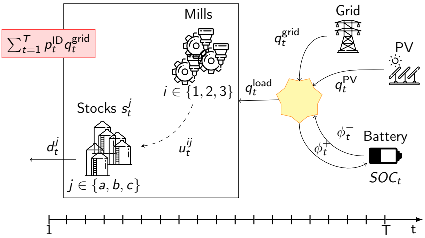
Design Problem

θ Parametrizes →

Day-ahead energy purchases

Battery sizing

Operational Problem



PRESENTATION OUTLINE

DESIGN PROBLEM

Design Problem Formulation

$$(\text{P}): \quad \min_{\theta \in \Theta} \quad I(\theta) + V(x_0; \theta)$$

- Design variables: $\theta := \{v_t^{\text{DA}}\}_{t \in [T]}$
- Design constraints: $\Theta := \quad \left\{ v_t^{\text{DA}} \geq 0, \quad \forall t \in [T] \right\}$

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- Design variables: $\theta := \{v_t^{\mathrm{DA}}\}_{t \in [T]}$
- Design constraints: $\Theta := \quad \{v_t^{\mathrm{DA}} \geq 0, \quad \forall t \in [T]\}$
- Design cost: $I(\theta) = \sum_{t=1}^{T} p_t^{\mathrm{DA}} v_t^{\mathrm{DA}}$;
- Parametrized problem cost: $V(x_0, \theta) := v(\mathrm{P}_\theta)$;

PRESENTATION OUTLINE

OPERATIONAL PROBLEM

Stochastic parametrized operational problem

$$(\mathrm{P}_\theta) \quad \min_{(\boldsymbol{u}_t, \boldsymbol{x}_t)_{t\in[T]}} \quad \mathbb{E}\left[\sum_{t=1}^{T} L_t^\theta(\boldsymbol{x}_{t-1}, \boldsymbol{u}_t, \boldsymbol{q}_t^{\mathrm{PV}})\right]$$

- State variables: $\boldsymbol{x_t} := (SOC_t, s_t^1, s_t^2, s_t^3)$,
- Controls: $\boldsymbol{u_t} := (\underbrace{q_t^{\mathrm{grid}}, v_t^{\mathrm{ID}}, \phi_t^+, \phi_t^-, (u_t^{ij})_{i\in I, j\in J}}_{\in\mathbb{R}^+}, \underbrace{(b_t^{ij})_{i\in I, j\in J}}_{\in\{0,1\}})$,
- Random variables : $\boldsymbol{q_t}^{\mathrm{PV}}$ assumed independent.

OPERATIONAL PROBLEM

Stochastic parametrized operational problem

$$(\mathrm{P}_\theta) \quad \min_{(\boldsymbol{u}_t, \boldsymbol{x}_t)_{t \in [T]}} \quad \mathbb{E}\left[\sum_{t=1}^{T} L_t^\theta(\boldsymbol{x}_{t-1}, \boldsymbol{u}_t, \boldsymbol{q}_t^{\mathrm{PV}})\right]$$

$$\text{s.c} \quad x_t = \mathrm{D}_t^\theta(\boldsymbol{x}_{t-1}, \boldsymbol{u}_t, \boldsymbol{q}_t^{\mathrm{PV}})$$

- Dynamic equations:

$$\mathrm{D}_t^\theta(\boldsymbol{x}_{t-1}, \boldsymbol{u}_t, \boldsymbol{q}_t^{\mathrm{PV}}) = \begin{cases} s_t^j = s_{t-1}^j - d_t^j + \sum_i u_t^{ij} & \forall j \\ SOC_t = SOC_{t-1} - \rho\phi_t^- + \rho\phi_t^+ \end{cases}$$

- Initial conditions : $s_0 = 0 \; SOC_0 = SOC_{min}$

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$$\text{s.c} \quad x_t = \mathrm{D}_t^\theta(\boldsymbol{x}_{t-1}, \boldsymbol{u}_t, \boldsymbol{q}_t^{\mathrm{PV}}) \qquad x_t \in X_t^\theta \qquad \forall t \in [T]$$

- State variables' feasible domain:

$$X_t^\theta = \begin{cases} 0 \leq s_t^j \leq s_{max}^j & \forall j \in J \\ SOC_{min} \leq SOC_t \leq SOC_{max} & \end{cases}$$

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$$u_t \in \mathcal{U}_t^\theta(\boldsymbol{x}_{t-1}, \boldsymbol{q}_t^{\mathrm{PV}}) \subset U_t^\theta \qquad \forall t \in [T]$$

- Feasible domain of controls:

$$\mathcal{U}_t^\theta(\boldsymbol{x}_{t-1}, \boldsymbol{q}_t^{\mathrm{PV}}) = \begin{cases} \boldsymbol{b}_t^{ij} \in \{0, 1\} & \forall i \in I, j \in J \\ u_{min}^{ij} b_t^{ij} \leq u_t^{ij} \leq u_{max}^{ij} b_t^{ij} & \forall i \in I, j \in J \\ q_t^{\mathrm{grid}}, v_t^{\mathrm{ID}}, \phi_t^+, \phi_t^- \geq 0 & \\ \phi_t^+ \leq \phi_{max}^+ \quad \phi_t^- \leq \phi_{max}^- & \\ \dots & \end{cases}$$

OPERATIONAL PROBLEM

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\begin{aligned}
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& \qquad\;\; u_t \in \mathcal{U}_t^\theta(\boldsymbol{x}_{t-1}, \boldsymbol{q}_t^{\mathrm{PV}}) \subset U_t^\theta \qquad \forall t \in [T]
\end{aligned}
$$

- Controls constraints:

$$
\mathcal{U}_t^\theta(\boldsymbol{x}_{t-1}, \boldsymbol{q}_t^{\mathrm{PV}}) = \begin{cases} \dots \\ \sum_j b_t^{ij} \leq 1 & \text{1 product per mill} \\ \max_i b_t^{ia} + \max_i b_t^{ic} \leq 1 & \text{Shared resources} \\ q_t^{\mathrm{load}} \leq q_t^{\mathrm{grid}} + q_t^{\mathrm{PV}} + \phi_t^- - \phi_t^+ & \text{Load balance} \\ q_t^{\mathrm{grid}} = v_t^{\mathrm{DA}} + v_t^{\mathrm{ID}} & \text{Energy purchases} \end{cases}
$$

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& u_t \in \mathcal{U}_t^\theta(\boldsymbol{x}_{t-1}, \boldsymbol{q}_t^{\mathrm{PV}}) \subset U_t^\theta \qquad \forall t \in [T] \\
& \sigma(u_t) \subset \sigma(\boldsymbol{q}_1^{\mathrm{PV}}, ..., \boldsymbol{q}_t^{\mathrm{PV}}) \qquad \forall t \in [T]
\end{aligned}
$$

- Objective: we minimize the expected cost over $[1, \dots, T]$;
- Instantaneous cost: $L_t^\theta(\boldsymbol{x}_{t-1}, \boldsymbol{u}_t, \boldsymbol{q}_t^{\mathrm{PV}}) := p_t^{\mathrm{ID}} v_t^{\mathrm{ID}}$;
- Non-anticipativity constraints: we don't know what happens in the future (after t).

PRESENTATION OUTLINE

THE (CORRECTED) EV STRATEGY

- Solve the Expected Value problem (EV),

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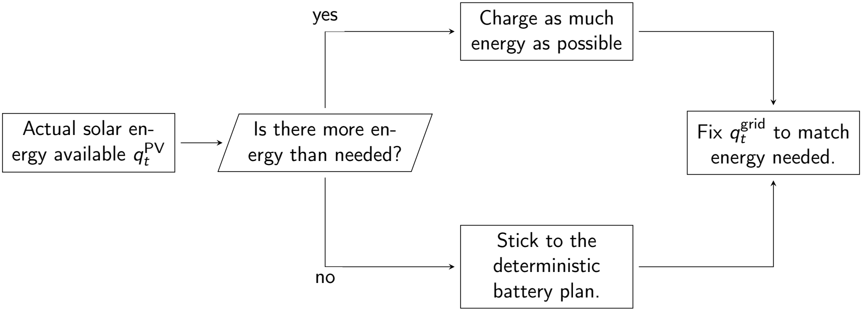

Figure: Deterministic procedure to adapt variables to uncertainties.

PRESENTATION OUTLINE

MODEL PREDICTIVE CONTROL

Algorithm 1: Model predictive control

Input: x_0, $\hat{q}^{PV}$ solar prediction for the whole horizon

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    Observe $\boldsymbol{q}_t^{\mathrm{PV}}$ realization of solar energy t.

MODEL PREDICTIVE CONTROL

Algorithm 1: Model predictive control

1 **Input:** x_0, $\hat{q}^{PV}$ solar prediction for the whole horizon
2 **for** t : 1,...,T **do**
3 Observe q_t^{PV} realization of solar energy t.

$$(u^\sharp_{t'})_{t'\geq t} = \underset{u_t,(u_{t'})_{t'>t}}{\arg\min}\; L_t(x_{t-1}, u_t, q_t^{\mathrm{PV}}) + \sum_{t'=t+1}^{T} L_t(x_{t'-1}, u_{t'}, \hat{q}^{PV}_{t'})$$

$$x_{t'} = D_t(x_{t'-1}, u_{t'}) \in \mathbb{X}_{t'}$$

$$u_{t'} \in \mathbb{U}_{t'}(x_{t'}, \hat{q}^{PV}_{t'})$$

MODEL PREDICTIVE CONTROL

Algorithm 1: Model predictive control

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for t : 1,...,T **do**

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$$
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(u^\sharp_{t'})_{t' \geq t} = \operatorname*{arg\,min}_{u_t, (u_{t'})_{t'>t}} \; & L_t(x_{t-1}, u_t, q_t^{\mathrm{PV}}) + \sum_{t'=t+1}^{T} L_t(x_{t'-1}, u_{t'}, \hat{q}_{t'}^{PV}) \\
& x_{t'} = D_t(x_{t'-1}, u_{t'}) \in \mathbb{X}_{t'} \\
& u_{t'} \in \mathbb{U}_{t'}(x_{t'}, \hat{q}_{t'}^{PV})
\end{aligned}
$$

$$x_t = D_t(x_{t-1}, u_t^\sharp)$$

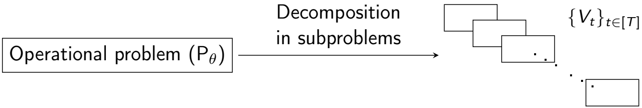
PRESENTATION OUTLINE

DYNAMIC PROGRAMMING

Operational problem (P_θ)

Large multistage stochastic mixed-integer problem

DYNAMIC PROGRAMMING



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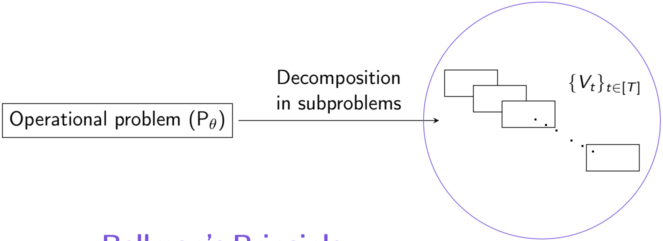
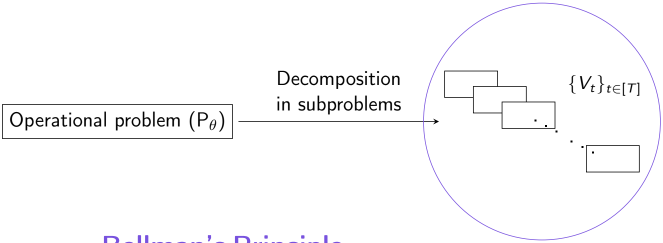


Bellman's Principle

$V_t(x)$: optimal expected cost on $[\![t, T]\!]$ from state x

DYNAMIC PROGRAMMING



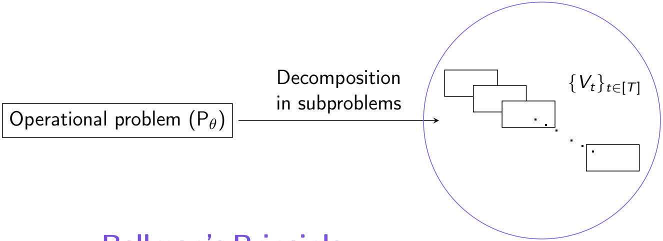
Bellman's Principle

$$\hat{V}_t(x,\xi) = \min_{u_t \in \mathcal{U}_t(x,\xi)} \underbrace{L_t^\theta(x,u_t,\xi)}_{\text{instantaneous cost}} + \underbrace{V_{t+1}(y)}_{\text{cost-to-go}}$$

$$y = \mathrm{D}_t^\theta(x,u_t,\xi)$$

$$V_t(x) = \mathbb{E}\left[\hat{V}_t(x,\boldsymbol{q}_t^{\mathrm{PV}})\right]$$

DYNAMIC PROGRAMMING



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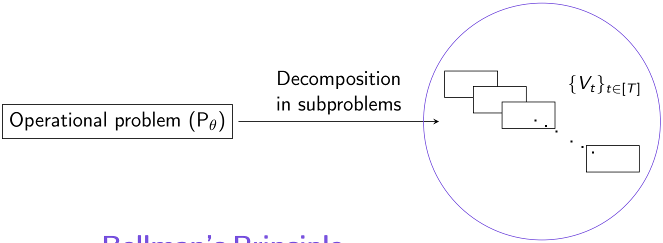
→ Hard to compute in practice

DYNAMIC PROGRAMMING



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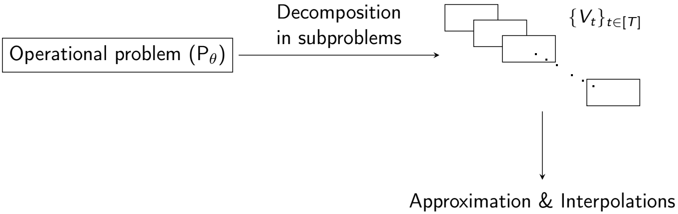
→ Hard to compute in practice

→ Curse of dimensionality

DYNAMIC PROGRAMMING



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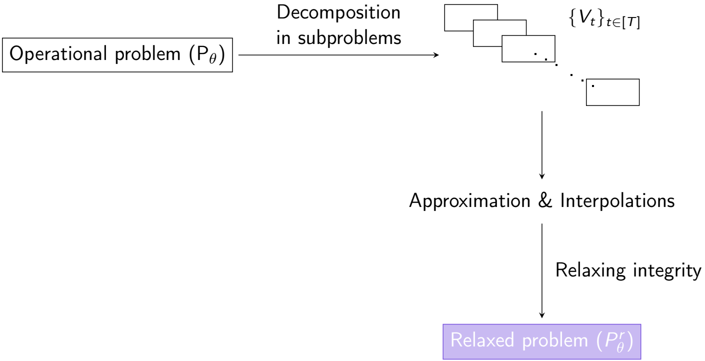
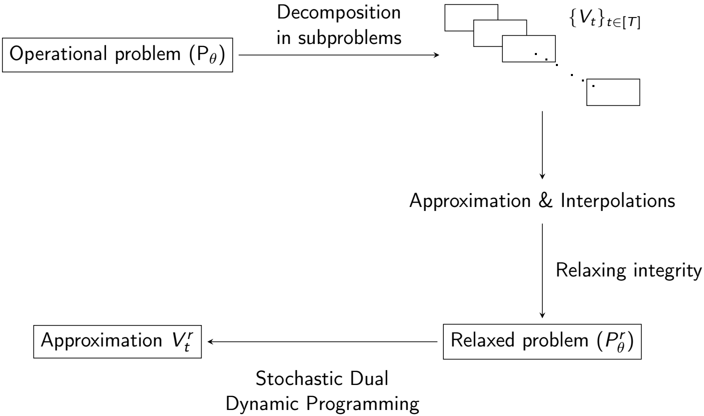


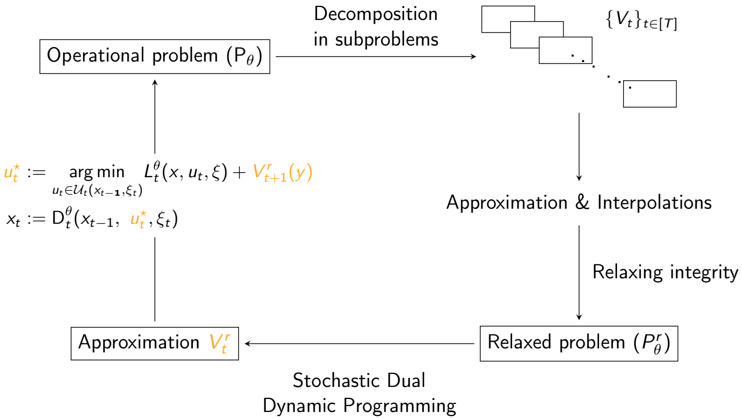
Large multistage stochastic continuous problem

DYNAMIC PROGRAMMING



Can we use these approximations to compute a feasible solution?

DYNAMIC PROGRAMMING



Can we use these approximations to compute a feasible solution?

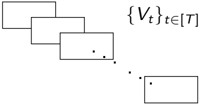
PRESENTATION OUTLINE

LOOK-AHEAD STRATEGY

Dynamic Programming

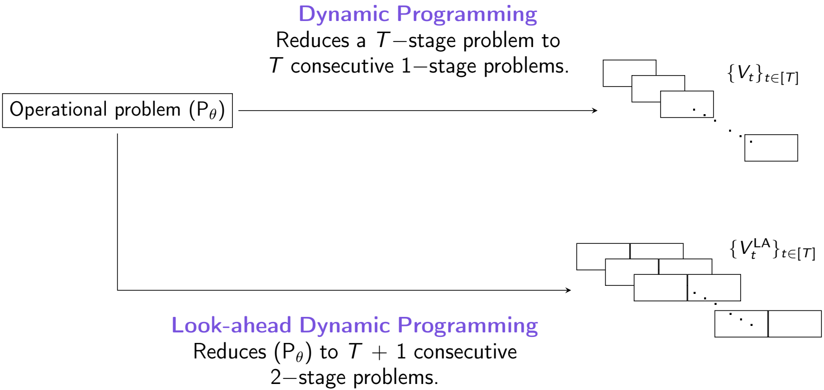
Reduces a $T-$stage problem to
T consecutive $1-$stage problems.

Operational problem (P_θ) →



$\{V_t\}_{t\in[T]}$

LOOK-AHEAD STRATEGY



LOOK-AHEAD STRATEGY

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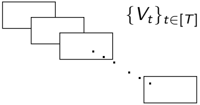

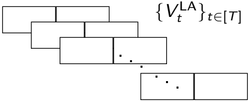

Look-ahead Dynamic Programming
Reduces (P_θ) to $T+1$ consecutive $2-$stage problems.

Non-anticipativity constraints must hold:
we consider all realizations and corresponding variables at $t+1(\times|\Omega_t|)$

LOOK-AHEAD STRATEGY

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Reduces a $T-$stage problem to
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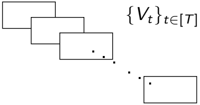
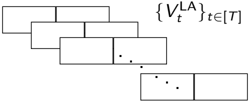
Operational problem (P_θ)





Look-ahead Dynamic Programming
Reduces (P_θ) to $T+1$ consecutive
$2-$stage problems.

- Non-anticipativity constraints must hold:
we consider all realizations and corresponding variables at $t+1(\times|\Omega_t|)$
- Objective: minimize the sum of instantaneous cost at t,
expected cost over scenarios at $t+1$ and expected cost-to-go from $t+2$.

PRESENTATION OUTLINE

SOLVING THE DESIGN PROBLEM

$$(\mathsf{P}): \quad \min_{\theta \in \Theta} \quad I(\theta) + V(x_0; \theta)$$

SOLVING THE DESIGN PROBLEM

$$(\mathrm{P}): \quad \min_{\theta \in \Theta} \quad I(\theta) + V(x_0; \theta)$$

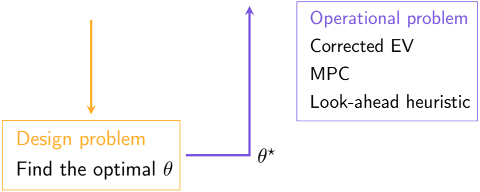
↓

Design problem

Find the optimal θ

SOLVING THE DESIGN PROBLEM

$$(\mathrm{P}): \quad \min_{\theta \in \Theta} \quad I(\theta) + V(x_0; \theta)$$



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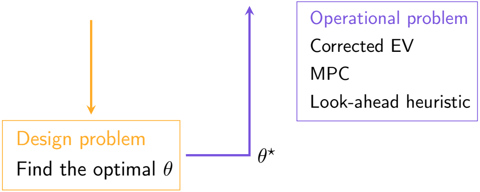

How to determine the optimal θ?

SOLVING THE DESIGN PROBLEM

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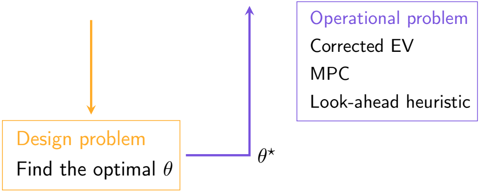


How to determine the optimal θ?

1. Expected Value strategy: solves a deterministic version of the whole problem to determine θ;
2. 2−stage strategy: takes decision θ minimizing the expected cost over S_{MC} scenarios;
3. Stochastic Dual Dynamic Programming: solves the continuous relaxation of the problem.

PRESENTATION OUTLINE

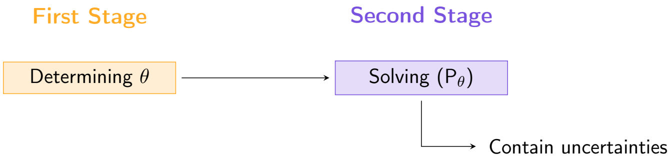
2−STAGE STRATEGY

First Stage

Determining θ

2–STAGE STRATEGY

2–STAGE STRATEGY



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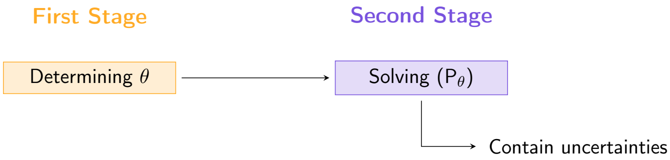
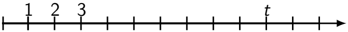


(P_θ) is a Multistage Problem.



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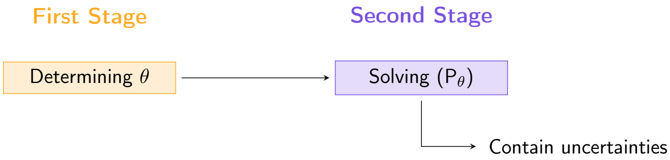

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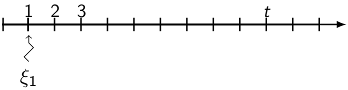

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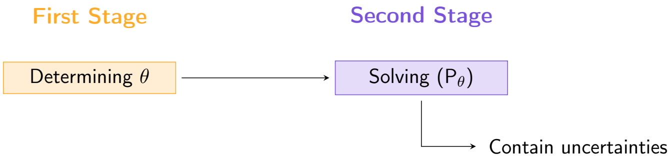

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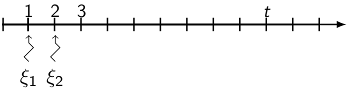

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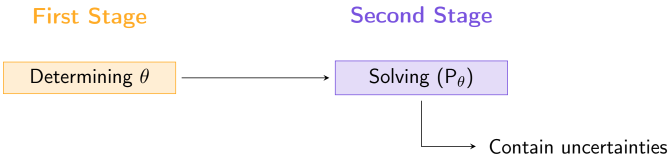

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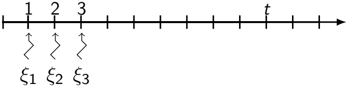

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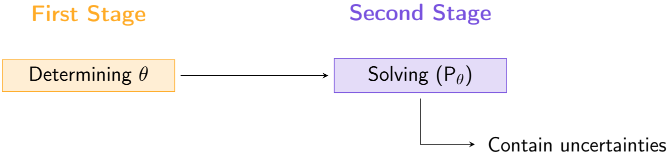

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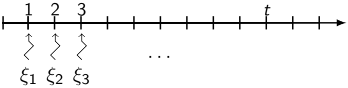

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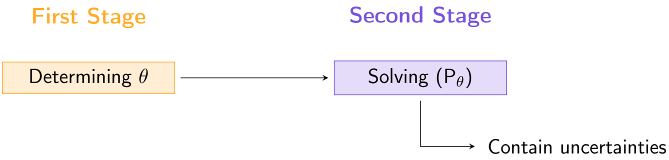

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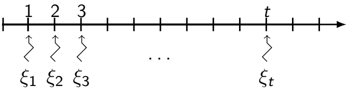


2−STAGE STRATEGY

First Stage

Determining θ →

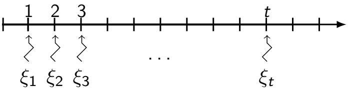
Second Stage

Solving (P_θ)

→ Contain uncertainties

(P_θ) is a Multistage Problem.

→ Here we consider it as a 1−stage problem.



2−STAGE STRATEGY

First Stage — Determining θ → **Second Stage** — Solving (P_θ)

↳ Contain uncertainties

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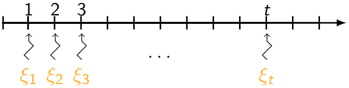

All uncertainties are revealed simultaneously

2−STAGE STRATEGY

First Stage — Determining θ → **Second Stage** — Solving (P_θ)

→ Contain uncertainties

(P_θ) is a Multistage Problem.

→ Here we consider it as a 1−stage problem.

→ $\min_{\theta \in \Theta} \mathbb{E}\left[V^{\text{ant}}(x_0, \boldsymbol{\xi}_{[1:T]}; \theta)\right]$

2−STAGE STRATEGY

First Stage

Determining θ

Must be chosen without knowing the uncertainties at stage 2

Second Stage

Solving (P_θ)

Contain uncertainties

(P_θ) is a Multistage Problem.

Here we consider it as a 1−stage problem.

$$\min_{\theta \in \Theta} \mathbb{E}\left[V^{\mathrm{ant}}(x_0, \boldsymbol{\xi}_{[1:T]}; \theta)\right]$$

2−STAGE STRATEGY

First Stage

Determining θ

Must be chosen without knowing the uncertainties at stage 2

$$\min_{\theta \in \Theta} \quad l(\theta) \; + \; \mathbb{E}[V^{\text{ant}}(x_0, \boldsymbol{\xi}_{[1:T]}; \theta)]$$

Second Stage

Solving (P_θ)

Contain uncertainties

(P_θ) is a Multistage Problem.

Here we consider it as a 1−stage problem.

$$\min_{\theta \in \Theta} \mathbb{E}\left[V^{\text{ant}}(x_0, \boldsymbol{\xi}_{[1:T]}; \theta)\right]$$

2−STAGE STRATEGY

First Stage

Determining θ → Solving (P_θ)

Must be chosen without knowing the uncertainties at stage 2

$$\min_{\theta\in\Theta} \quad l(\theta) + \mathbb{E}[V^{\text{ant}}(x_0, \boldsymbol{\xi}_{[1:T]}; \theta)]$$

SAA

$$\min_{\theta\in\Theta} \min_{(x_t^s, u_t^s)_{s,t}} \quad l(\theta) + \sum_{s=1}^{S} \frac{1}{S} V^{\text{ant}}(x_0, \xi^s_{[1:T]}; \theta)$$

Second Stage

Solving (P_θ) → Contain uncertainties

(P_θ) is a Multistage Problem.

Here we consider it as a 1−stage problem.

$$\min_{\theta\in\Theta} \mathbb{E}\left[V^{\text{ant}}(x_0, \boldsymbol{\xi}_{[1:T]}; \theta)\right]$$

TESTING FROM DATA

- Prices given by the Korea Electricity Power Corporation (KEPCO) website;
- Data collection for solar generation on NEDO website;
- Various renewable size, a factor $F \in \{0.5, 1, 2, 3\}$;
- Various battery sizing: SOC_{max} represents $0.5, 3$ or 6 hours of maximum renewable production;
- Final demand $d_T^j > 0$.

TESTING FROM DATA

Anticipative Regret (AR)

For a strategy ψ, and a scenario $\xi_{[T]}$,

$$AR^{\psi}(\xi_{[T]}) \;=\; \frac{\hat{V}^{\psi}(x_0, \xi_{[T]}; \theta) - \hat{V}^{\psi_{ant}}(x_0, \xi_{[T]}; \theta)}{|\hat{V}^{\psi_{ant}}(x_0, \xi_{[T]}; \theta)|}$$

OPERATIONAL PROBLEM RESULTS

SOC_{max}	0.5h			3h			6h		
Solar factor	L-A	MPC	EV	L-A	MPC	EV	L-A	MPC	EV
0.5	**4.9**	**0.5**	1.0	**6.1**	**0.5**	2.4	**5.4**	**0.5**	3.2
1.0	**6.1**	**1.3**	4.6	3.9	**0.9**	**6.3**	2.4	**0.6**	**6.4**
2.0	8.7	**3.9**	**14**	4.5	**1.5**	**15**	4.0	**1.4**	**15**
3.0	11	**5.6**	**27**	9.1	**3.6**	**28**	8.2	**3.5**	**28**

Table: Anticipative Regret (AR) in % for different methods (EV strategy, MPC, Look-ahead) for the operational problem: **MPC** yields the most satisfactory results.

PRESENTATION OUTLINE

DESIGN PROBLEM RESULTS

Solar Factor	OPT MPC	OPT 2stage	OPT SDDP	AR (in %) MPC	AR (in %) 2stage	AR (in %) SDDP
0.5	6067	**6023**	6038	1.6	**0.9**	1.1
1.0	5471	5483	**5451**	2.1	2.3	**1.7**
2.0	4552	4553	**4481**	4.2	4.2	**2.5**
3.0	3714	3691	**3641**	8.7	7.9	**6.7**

Table: Expected Cost (Opt) and Anticipative Regret (AR) for different methods (EV, 2−stage, SDDP) determining θ and then MPC.

IN A NUTSHELL

- We decompose an industrial energy-aware problem into an operational problem embedded in a design problem.
- We confront methods relaxing either integrity or information constraints.
- For these kinds of problems:
  - Considering uncertainties is relevant;
  - If uncertainties impact future costs, a stochastic method yields better results.

Future works

- Find a satisfactory stochastic heuristic dealing with binary variables;
- Incorporate energy market vision.

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