Smart Energy Systems
Winter 2020-2021

Optimization Project Group Final Presentation

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Agenda

1. Introduction
2. Problem description
3. Solution methodology
4. Results
5. Conclusion
6. Outlook

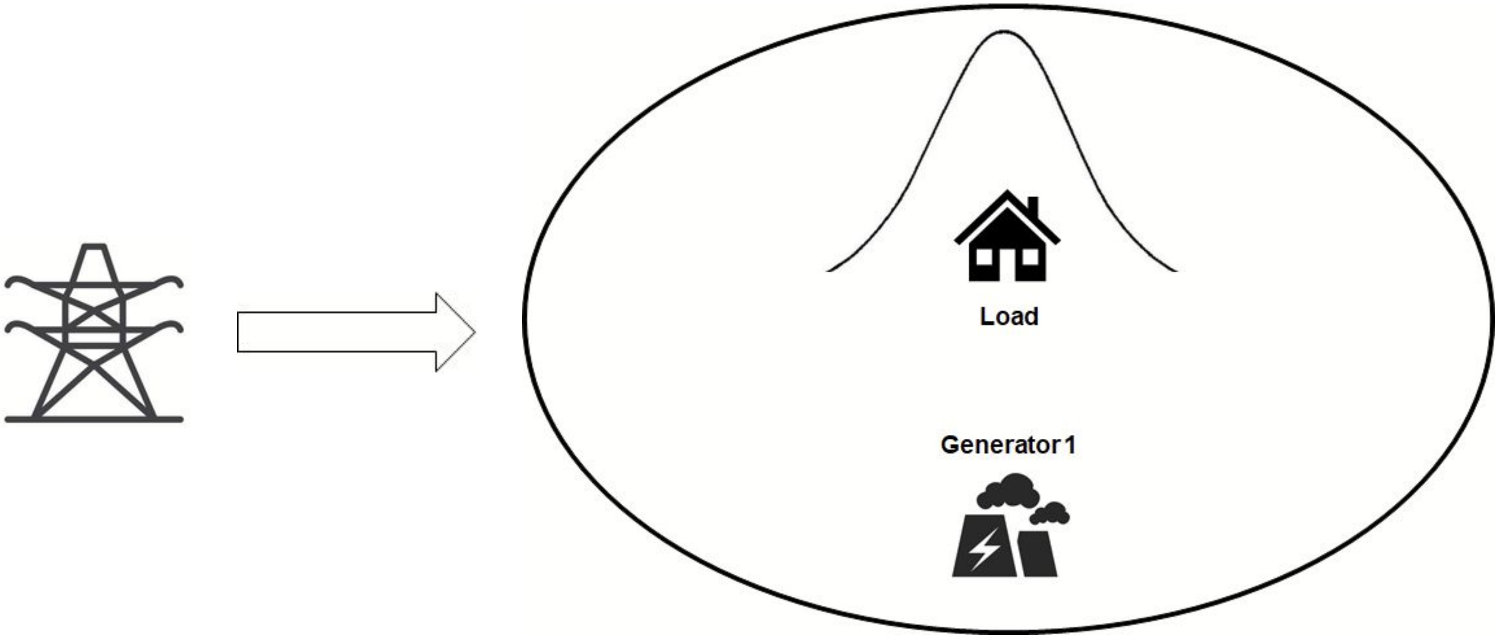
Introduction | Motivation

1. How can we optimally operate a microgrid under uncertainty?
2. How can we ensure efficiency of the operation in a two-staged problem?
3. How can we leverage variance reduction techniques in this modelling approach?

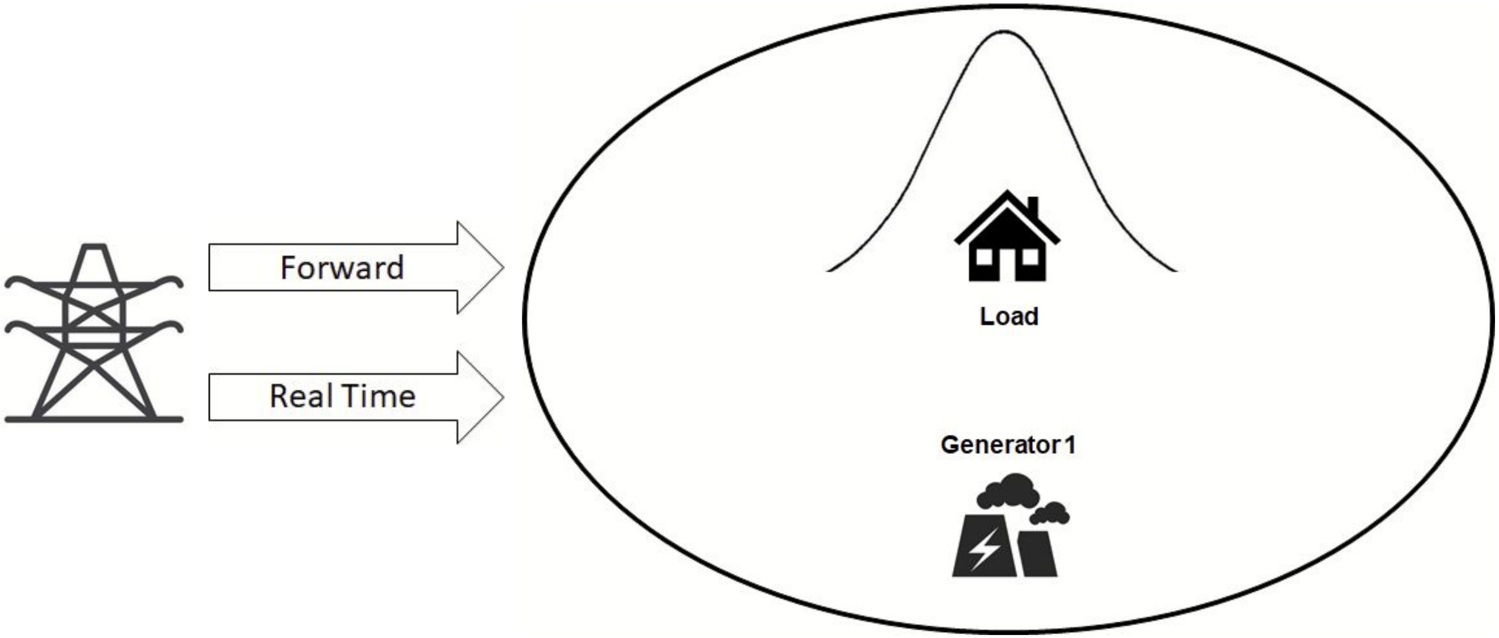
Introduction | Unit commitment

- Short-term planning of a microgrid is determined by unit commitment (UC) and economic dispatch decisions
- Sets start-up and shut-down of thermal generation resources while minimizing costs
- Based on expected load, equipment limitations, and operational policies

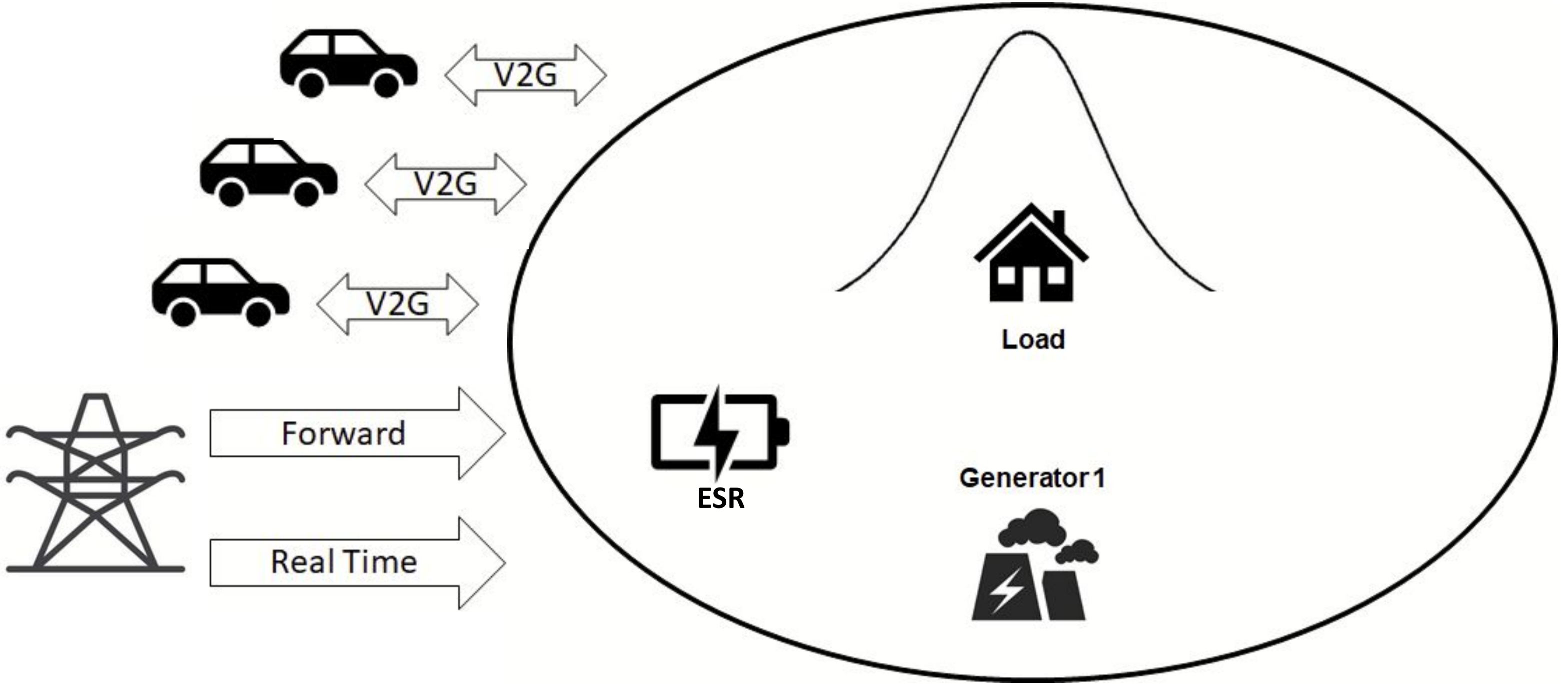
Problem description | Model set-up



Problem description | Model set-up



Problem description | Model set-up



Problem description | Objective function

$$\min_{u_G, p_{FW}, p_G, p_{RT}} \left(\sum_{h \in H} c_G^u * u_G[h] + \lambda_{FW} * p_{FW}[h] + E\left[c_G^p * p_G[h] + \lambda_{RT} * p_{RT}[h]\right] \right)$$

c_G^u	Fixed costs of generator	*0.0000212 $/h*	λ_{RT}	Price of real time contract (RT)	*0.3 $/kWh*
$u_G[h]$	Unit commitment of generator in hour *h*	-	$p_{RT}[h]$	Power purchased from RT in hour *h*	*kW*
λ_{FW}	Price of forward contract (FW)	*0.25 $/kWh*	c_G^p	Linear costs of generator	*0.128 $/kWh*
$p_{FW}[h]$	Power purchased from FW in hour *h*	*kW*	$p_G[h]$	Power generation of generator in hour *h*	*kW*

Source: Yurdakul et al. (2020)

Problem description | Generator

Characteristics:

$[p_G]^m$	Minimum power output	*0 kW*
$[p_G]^M$	Maximum power output	*12 kW*
$T_G^{\uparrow}$	Minimum uptime	*3 h*
$T_G^{\downarrow}$	Minimum downtime	*4 h*
R_G	Ramping	*5 kW*

Assumptions:

- Start generation with *0 kW*

Constraints:

$$u_G[h] * [p_G]^m \leq p_G[h] \leq u_G[h] * [p_G]^M$$

$$-R_G \leq p_G[h] - p_G[h-1] \leq R_G$$

$$u_G[h] - u_G[h-1] \leq u_G[\nu], \; \forall\, \nu \in N \text{ such that}$$
$$h \leq \nu \leq \min\left\{h - 1 + T_G^{\uparrow},\, H\right\}$$

$$u_G[h-1] - u_G[h] \leq 1 - u_G[\nu], \; \forall\, \nu \in N \text{ such that}$$
$$h \leq \nu \leq \min\left\{h - 1 + T_G^{\downarrow},\, H\right\}$$

$$\forall\, h \in H = \{0, \ldots, 24\}$$

Source: Yurdakul et al. (2020)

Problem description | Energy storage resource (ESR)

Characteristics:

$E^M_{\sigma_S}$	Minimum storage level	*0 kWh*
$E^m_{\sigma_S}$	Maximum storage level	*5 kWh*
$p^w_{\sigma_S}$	Maximum withdrawal power	*10 kW*
$p^i_{\sigma_S}$	Minimum charging power	*10 kW*
$E_{\sigma_S}[h]$	Storage level in hour *h*	*kWh*

Constraints:

$$E^m_{\sigma_S} \leq E_{\sigma_S}[h] \leq E^M_{\sigma_S}$$

$$E_{\sigma_S}[h] = E_{\sigma_S}[h-1] \; - \; P^{net}_{\sigma_S}[h] * 1h$$

$$-p^i_{\sigma_S} \leq P^{net}_{\sigma_S}[h] \leq p^w_{\sigma_S}$$

$$\forall \, h \in H$$

Assumptions:

- No losses, hence efficiency *100 %*
- No costs
- Initialize an empty storage

Source: Yurdakul et al. (2020)

Problem description | Electrical vehicle (EV)

Characteristics:

$E^M_{\sigma_S}$	Minimum storage level	*0 kWh*
$E^m_{\sigma_S}$	Maximum storage level	*38 kWh*
$p^w_{\sigma_S}$	Maximum withdrawal power	*11 kW*
$p^i_{\sigma_S}$	Minimum charging power	*11 kW*

Assumptions:

- Based on ESR
- Plugged in at *30 %* at hour *7*
- Plugged out at *60 %* at hour 17
- State of charge between *20 %* and *80 %*

Constraints:

$$0.2 * E^M_{\sigma_S} \leq E_{\sigma_S}[h] \leq 0.8 * E^M_{\sigma_S} \, \forall \, h \in \{7, \dots, 17\}$$

$$E_{\sigma_S}[7] = 0.3 * E^M_{\sigma_S} \; - \; P^{net}_{\sigma_S}[7]$$

$$E_{\sigma_S}[h] = E_{\sigma_S}[h-1] \; - \; P^{net}_{\sigma_S}[h] * 1h \, \forall \, h \in \{8, \dots, 17\}$$

$$E_{\sigma_S}[17] = 0.6 * E^M_{\sigma_S}$$

$$-p^i_{\sigma_S} \leq P^{net}_{\sigma_S}[h] \leq p^w_{\sigma_S} \, \forall \, h \in H$$

$$P^{net}_{\sigma_S}[h] \; = \; 0, \; E_{\sigma_S}[h] = 0 \, \forall \, h \; \in H \setminus \{7, \dots, 17\}$$

Source: Yurdakul et al. (2020)

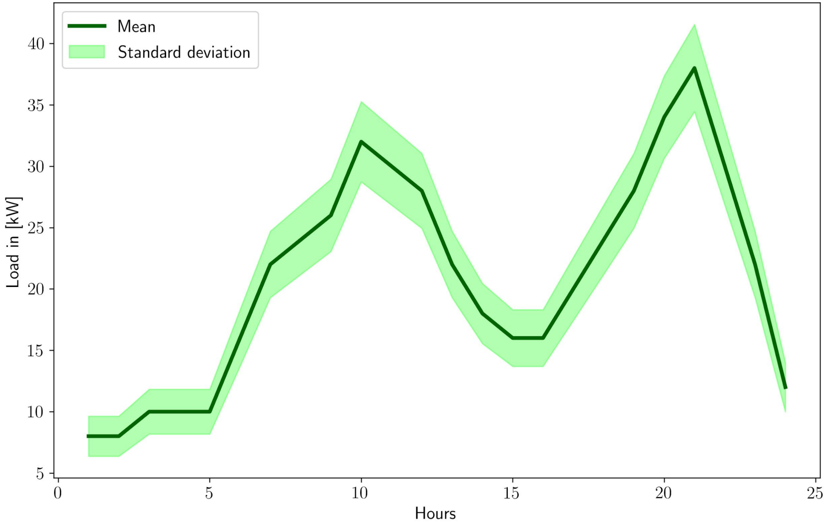
Problem description | Load

Constraints:

$$p_G[h] + p_{FW}[h] + p_{RT}[h] + \sum_{\sigma_S \in ESR} P^{net}_{\sigma_S}[h] \geq L[h] \, \forall h \in H$$

$L[h]$ Load value in hour *h* *kW*

Characteristics:



Assumptions:

- Hours independent, normally distributed
- Variance = ⅓ * mean

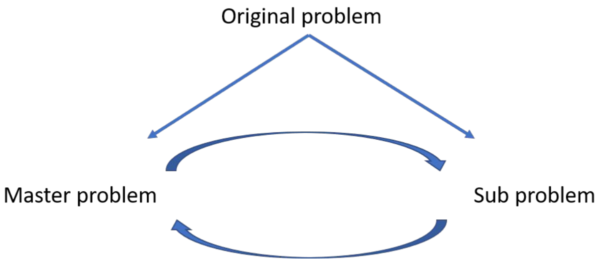
Source: Yurdakul et al. (2020)

Problem description | DAI-Labors testbed

- Optimization methods
    - Represent DAI-Labors testbed
    - Applicable to real life example
    - Scalable

Solution methodology | Characteristics

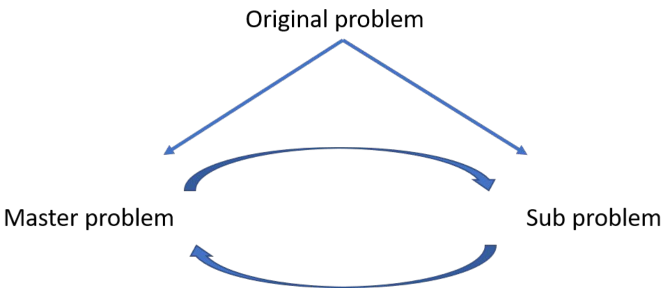
$$\min(c^T x)$$
$$s.t.\ Ax \leq b$$
$$x > 0$$

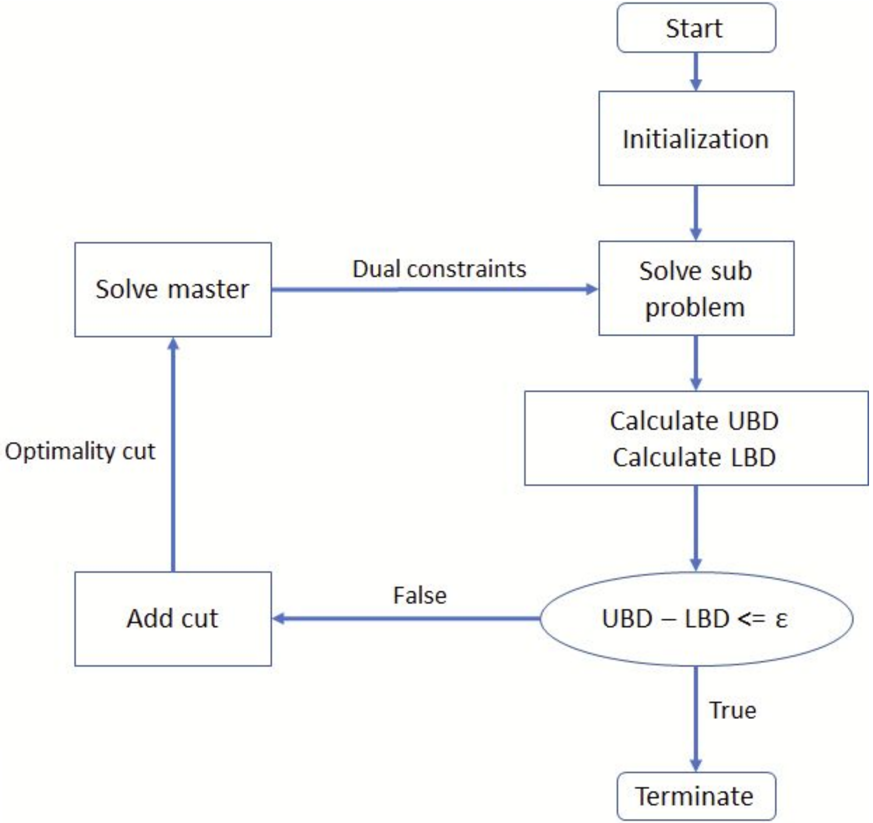


Solving for all samples simultaneously increases **computation time**

Split problem into **two stages** and solve iteratively

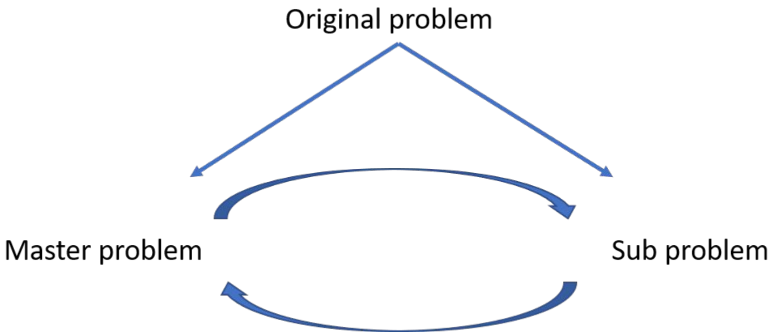
Solution methodology | L-shape method





The L-shaped Method

- decomposition into master and sub problem
- solve subproblem: complicating variables are treated as parameters to get a candidate solution
- insert optimality cut into the master problem
- optimality cut is a proxy for the 1st stage decision on 2nd stage costs
- master problem: lower bound (less constraints)
- sub problem: upper bound
- optimal solution when upper and lower bound are sufficiently close
- L-shaped method:
    - uncertainty
    - multiple subproblems



Solution methodology | Sampling techniques

- Goal: Decrease variance to get more accurate estimator of the mean
- Increasing sample size? ⚡ computation time
- Better: improving Monte Carlo samples through variance reduction techniques

→

1. **Latin Hypercube Sampling**
2. **Antithetic Variates**

Source: Homem-de-Mello & Bayraksan (2016)

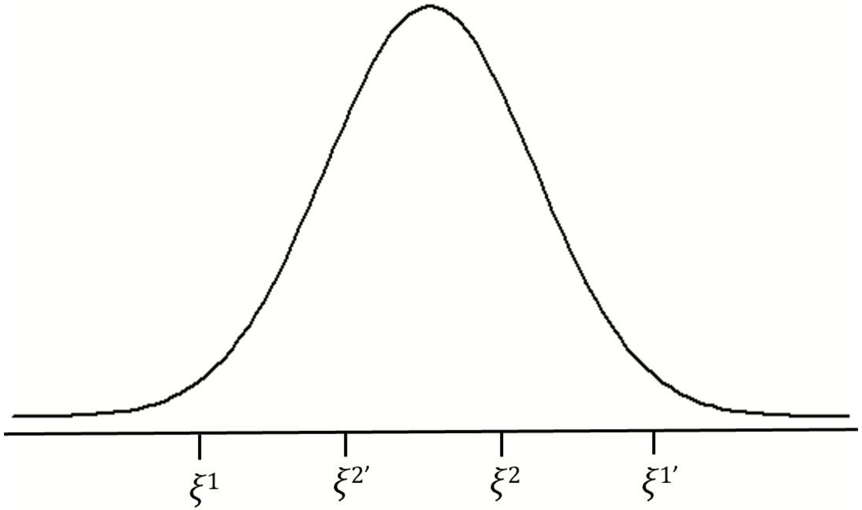
Antithetic variates | Implementation

- Idea: exploit correlations by pairing negatively correlated random variables

1. Create random samples with N = ½ sample size from a normal distribution (general case: from uniform distribution)

2. Calculate antithetics: mean values - (random samples - mean values)

3. Join the random samples and its antithetics to create the full sample



Source: based on Homem-de-Mello & Bayraksan (2016)

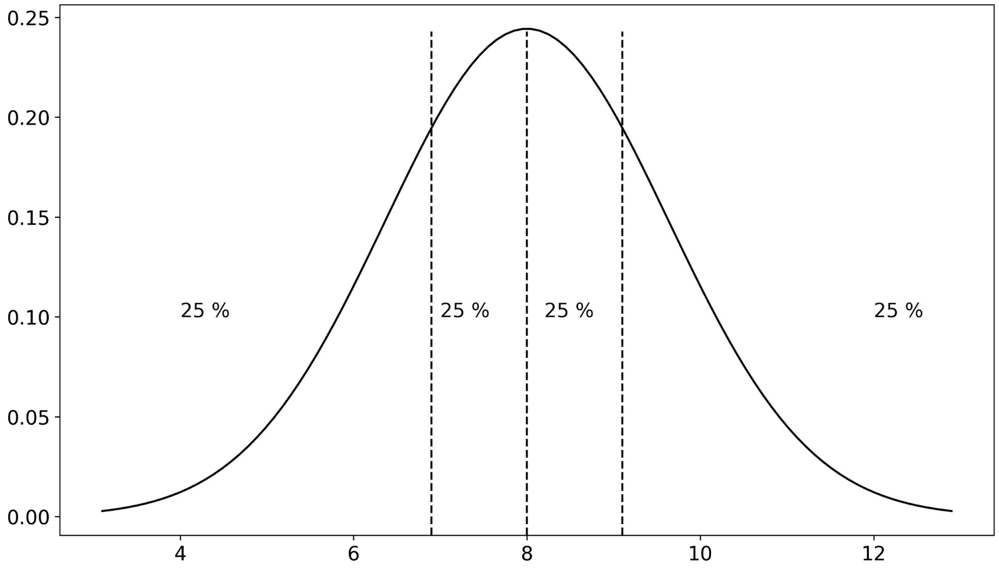
Latin hypercube | Implementation

1. For each hour, divide distribution into N parts of equal probability (N = sample size)

2. Draw a random sample from each part

3. Shuffle hourly sets

4. Create random vector from hourly sets



e.g. sample size = 4

Source: based on Homem-de-Mello & Bayraksan (2016)

Variance reduction | Implementation

Antithetic Variates

1. Create random samples with N = ½ sample size from a normal distribution
2. Calculate antithetics: mean values - (random samples - mean values)
3. Join the random samples and its antithetics to create the full sample

Latin Hypercube Sampling

1. For each hour, divide distribution into N parts of equal probability (N = sample size)
2. Draw a random sample from each part
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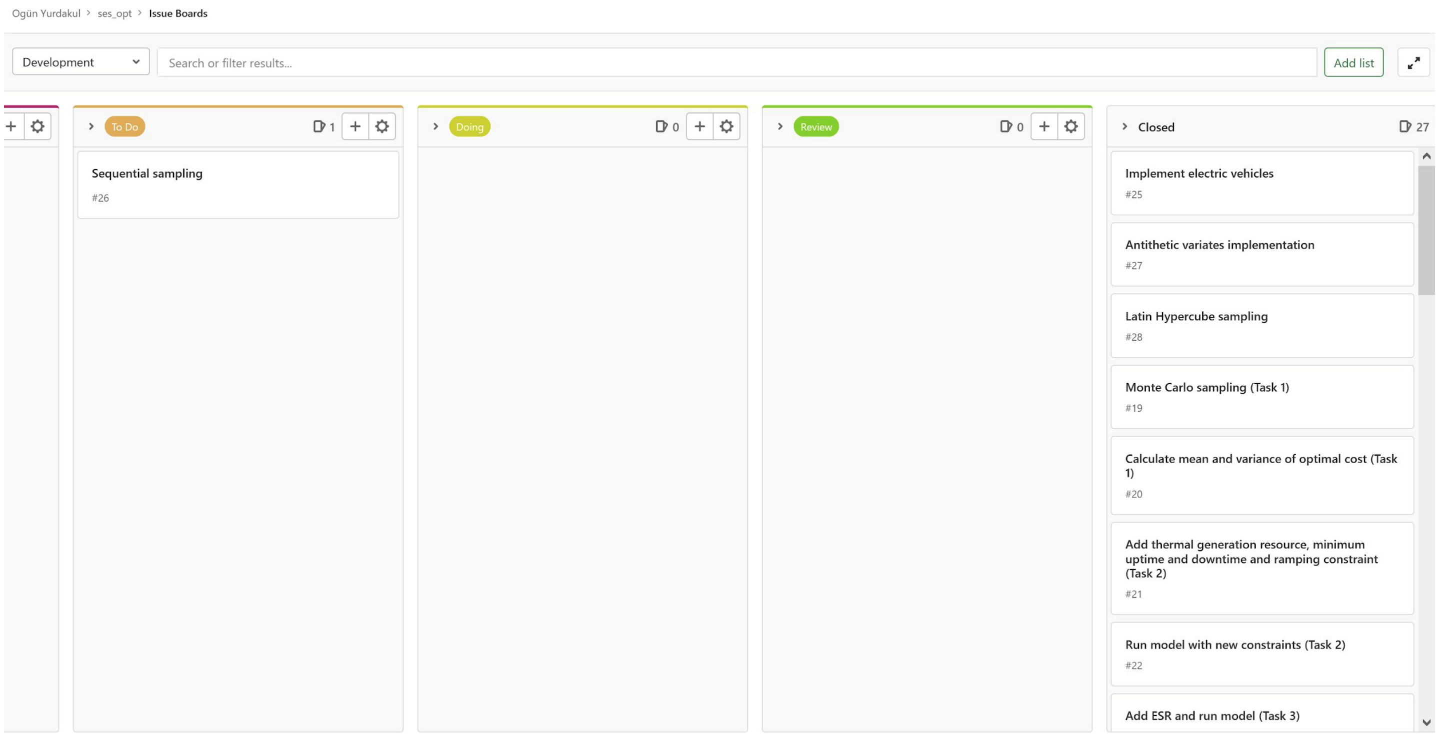
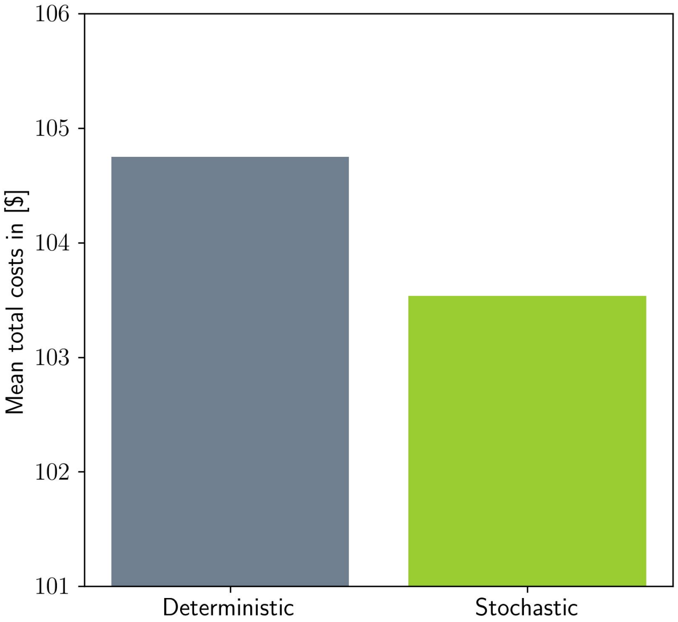
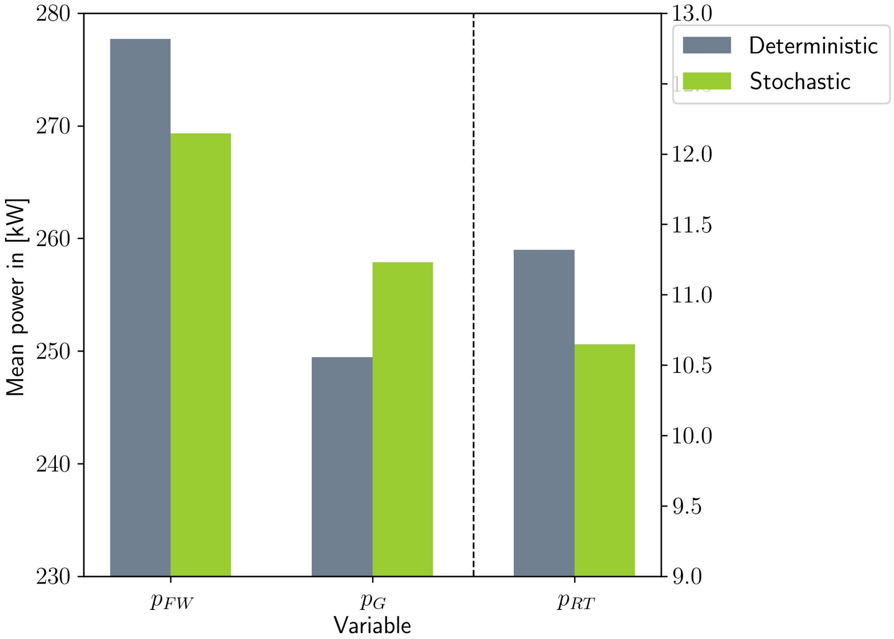
1. compare deterministic with stochastic approach (relation forward / real time)
2. Mean, variance, objective value (MS2)
3. Sample size & SD (MS3) → higher sample size decreases variance, computation time increases
4. MS 4: Variance reduction techniques & sample size
5. Final: Variance reduction techniques & sample size with new components
6. Computation time/ multiprocessing
7.

Scrum board

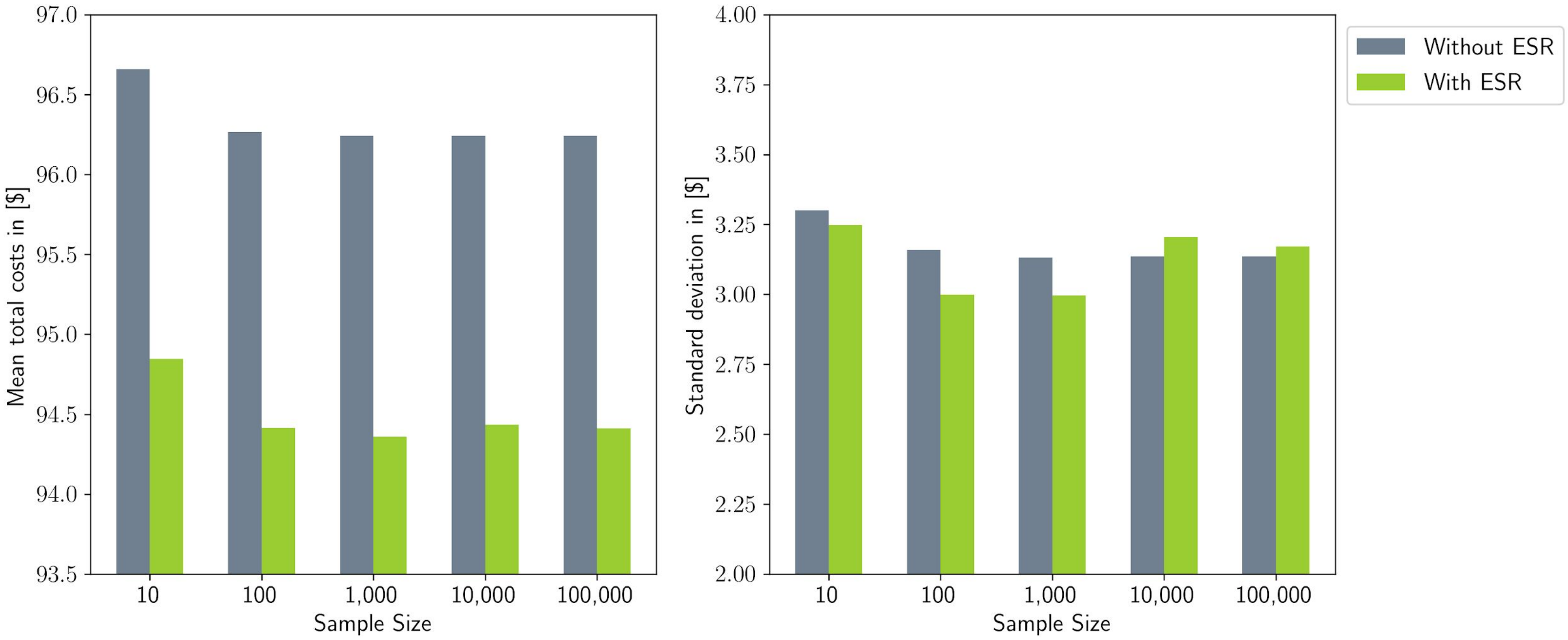

Ogün Yurdakul › ses_opt › Issue Boards
Development
Search or filter results...
Add list
To Do
1
Sequential sampling
#26
Doing
0
Review
0
Closed
27
Implement electric vehicles
#25
Antithetic variates implementation
#27
Latin Hypercube sampling
#28
Monte Carlo sampling (Task 1)
#19
Calculate mean and variance of optimal cost (Task 1)
#20
Add thermal generation resource, minimum uptime and downtime and ramping constraint (Task 2)
#21
Run model with new constraints (Task 2)
#22
Add ESR and run model (Task 3)

Results | Deterministic vs. stochastic

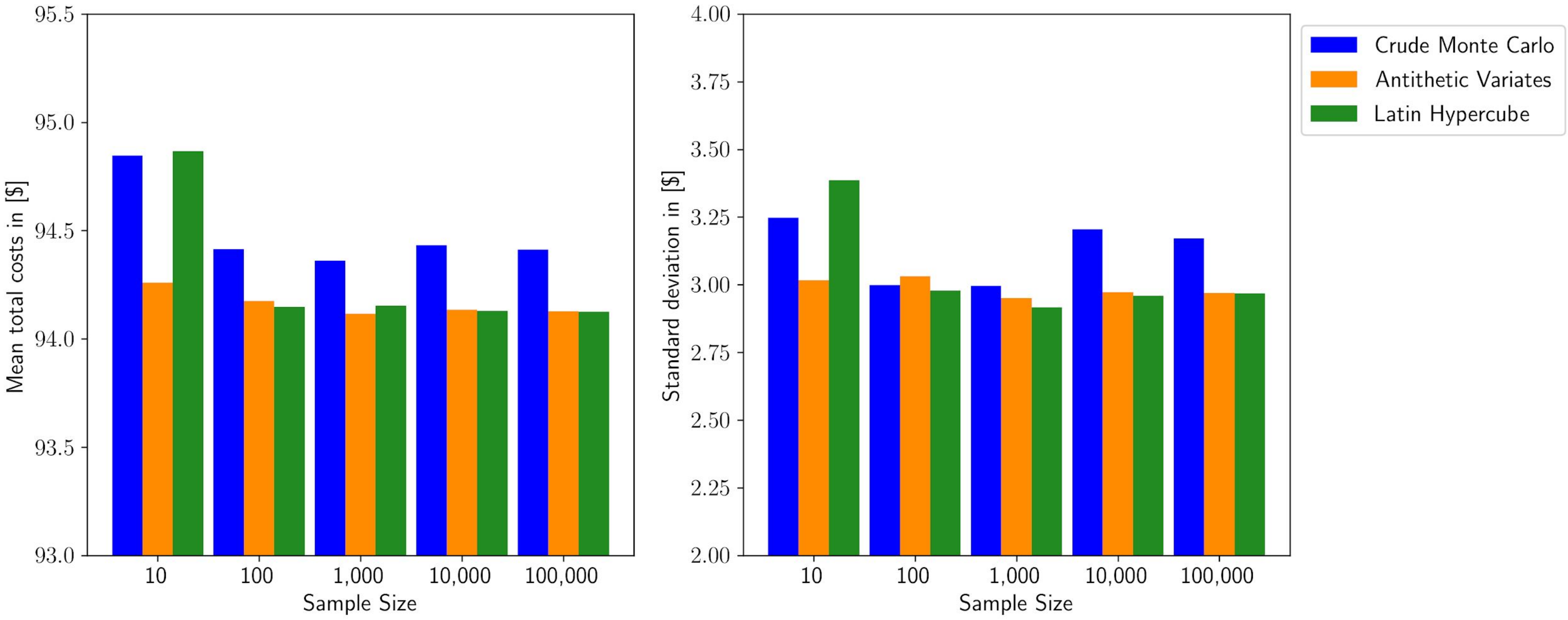




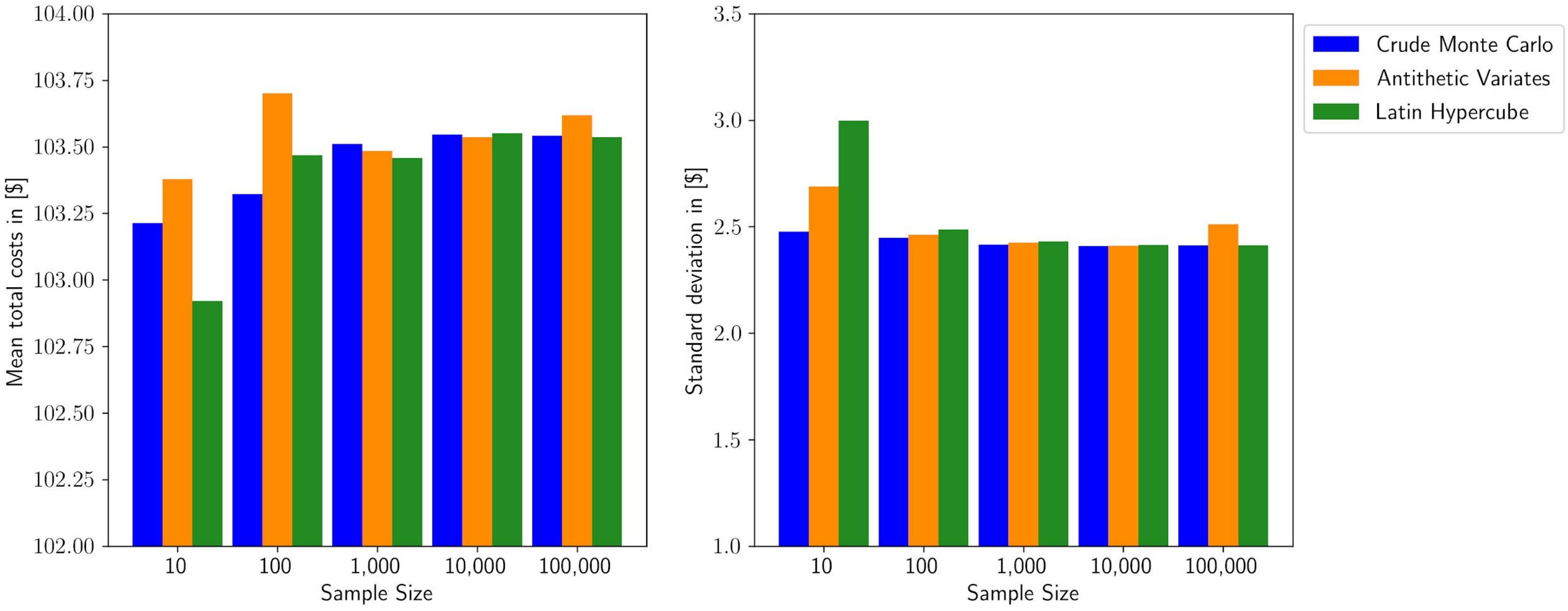
Results | Sample size



Results | Sampling techniques

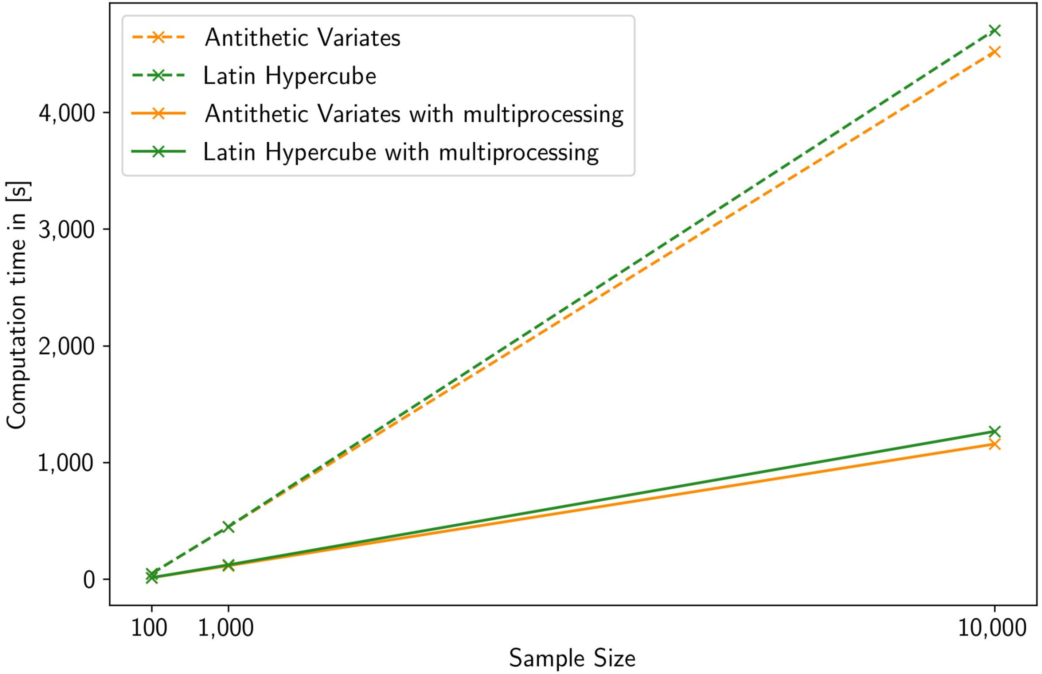


Results | Sampling techniques



Problematic: Equalities in constraints, negative recourse vector from second stage

Results | Computation time



Measures to improve runtime

- Remove unnecessary constraints
  - ↓ 5 %
- Execution via terminal
  - ↓ 20 %
- Enable multiprocessing
  - ↓ 75 %

Conclusion

- Stochastic approach yields better objective value
- Variance reduction techniques decrease the standard deviation in scenarios with no ESR
  - This effect does not yield with ESR: constraints violate the pre-conditions for Antithetic Variates and Latin Hypercube Sampling (no monotonicity)
- Structure of L-shaped method enables parallelization of tasks, facilitating multiprocessing to decrease processing time

Outlook

- Economic mechanisms
- Distribution and variability of load throughout seasons
- Further application of variance reduction techniques in optimization problems
- Avoidance of overly conservative sample sizes while assuring quality of solution → sequential sampling

References

Birge, J. R., and Louveaux, F., *Introduction to stochastic programming*. Springer Science & Business Media, 2011.

Conejo, A. J., Castillo, E., Minguez, R., and Garcia-Bertrand, R., *Decomposition techniques in mathematical programming: engineering and science applications*. Springer Science & Business Media, 2006.

Homem-de-Mello T. and Bayraksan, G., *Scenario Generation and Sampling Methods,* Lecture Slides, 2016. Accessible via https://www.youtube.com/watch?v=RkUdWL_3KLA

Yurdakul et al., *Quantification of the Impact of GHG Emissions on Unit Commitment in Microgrids,* in IEEE PES T&D-LA 2020.

Thanks for your attention

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