Smart Energy Systems
Winter 2020-2021

Optimization Project Group
Milestone 4

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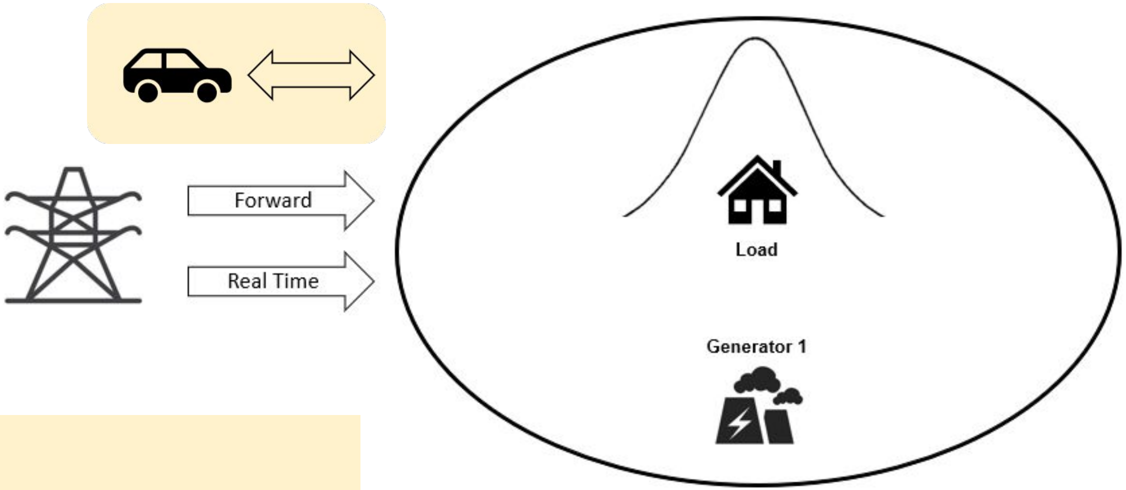
Agenda

- Recap: Stochastic Unit Commitment
- Variance Reduction Techniques
    - Antithetic Variates
    - Latin Hypercube Samples
- Influence of Multiprocessing
- Electric Vehicle

Recap: Stochastic Unit Commitment

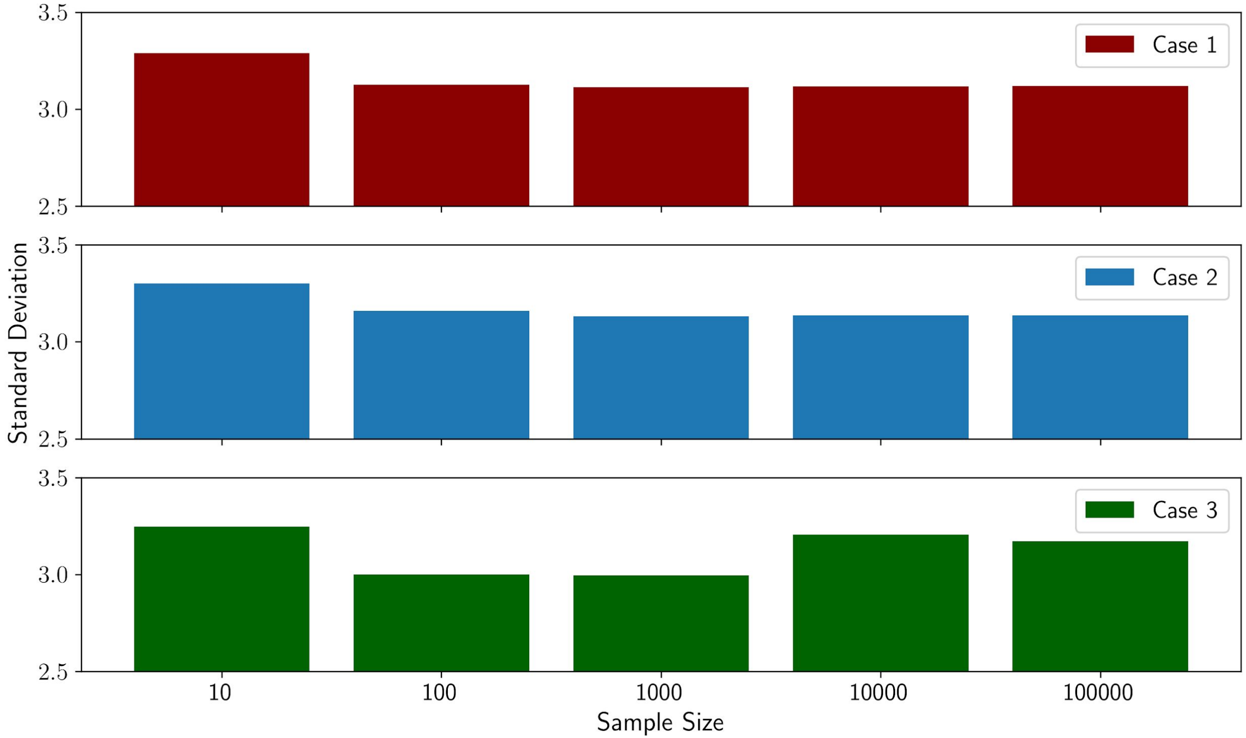
- Optimization of dispatch schedule of all power generation units to match the electricity demand and to minimize total cost
- Two-staged optimization



New:

- Reduce variance without increasing sample size
- Assess the influence of multiprocessing on runtime
- Electric vehicle with vehicle-to-grid technology (V2G)

Milestone 3: Standard deviation



Variance reduction techniques

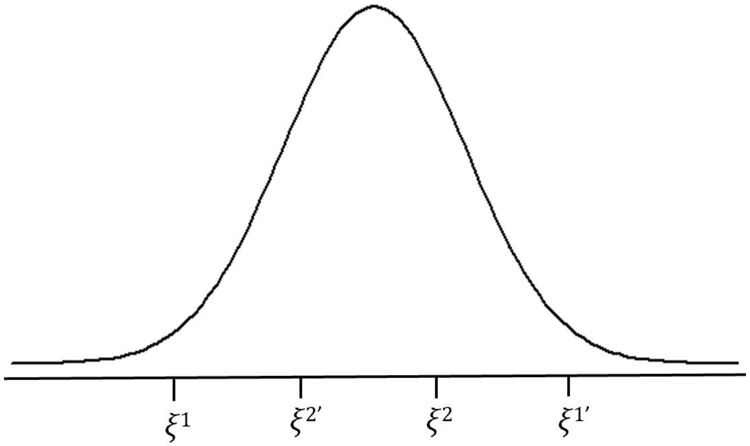
- Goal: decrease variance to get more accurate estimator of the mean
- Increasing sample size? ⚡ computation time
- Better: improving Monte Carlo samples through variance reduction techniques
- Common ideas:
  - Making use of correlations
  - Sampling input space more uniformly than random sampling
  - Focus on important regions for sampling

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

Antithetic Variates

- Idea: exploit correlations by pairing negatively correlated random variables

1. Sample N/2 observations from a uniform distribution
2. Calculate antithetic pairs as [1 - sample from step 1]
3. Take inverse cumulative distribution function to obtain N observations

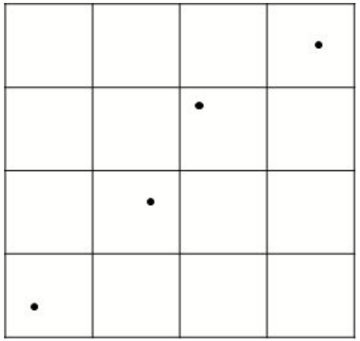


Source: based on Homem-de-Mello & Bayraksan (2016)

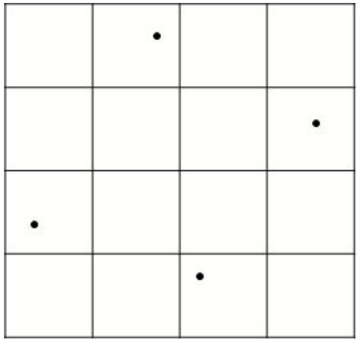
Latin Hypercube Sampling

- Idea: sample more uniformly than random sampling

1. Sample from a stratified input space
2. Randomly permute these observations
3. Take the inverse cumulative distribution function to obtain N observations



Stratify

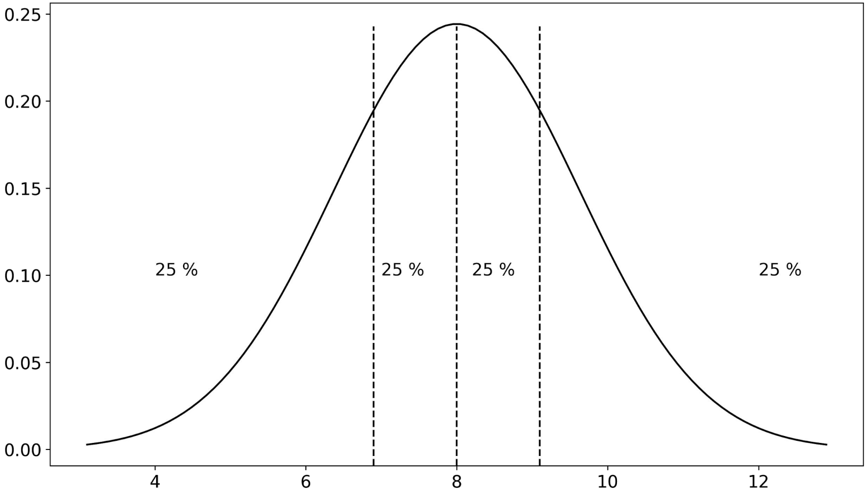


Permute

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

Latin Hypercube Sampling

1. Sample from a stratified input space
2. Randomly permute these observations
3. Take the inverse cumulative distribution function to obtain N observations



e.g. sample size = 4

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

Variance reduction | Implementation

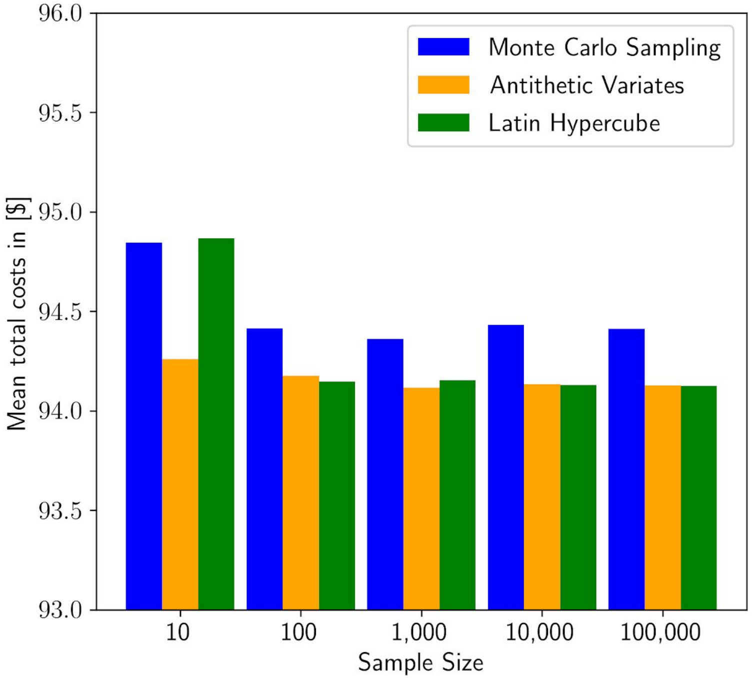
Antithetic Variates

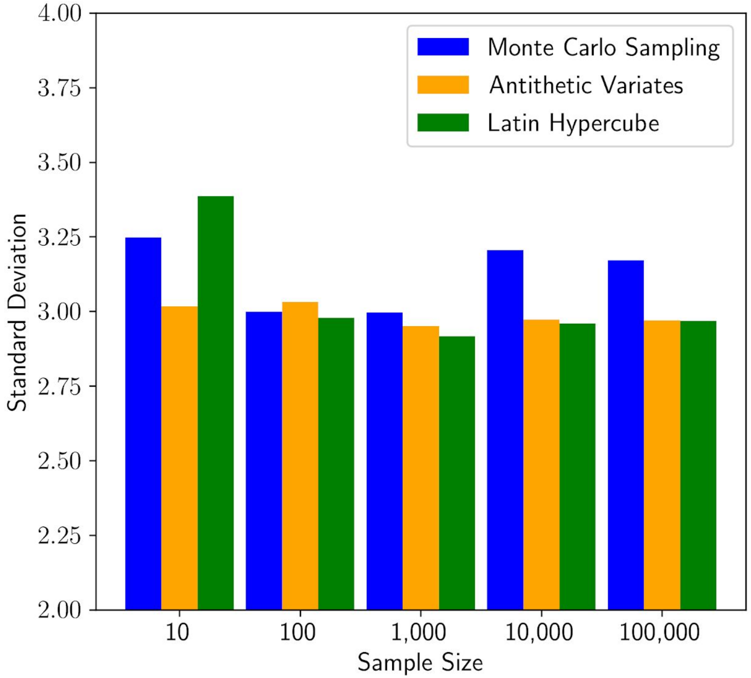
1. Create random samples with N = ½ sample size from a normal distribution
2. Calculate antithetics: mean values - (random samples - mean values)
3. Join the random samples and its antithetics to create the full sample

Latin Hypercube Sampling

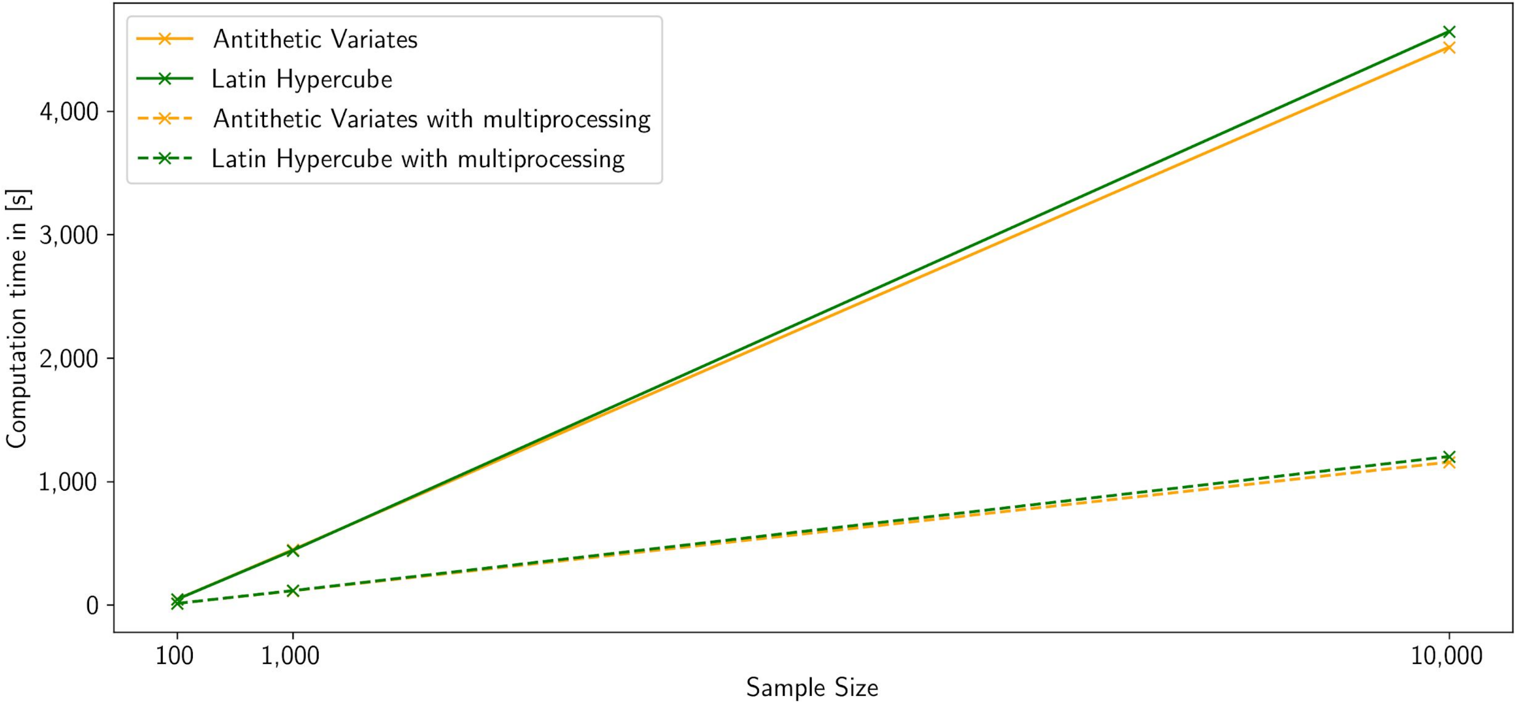
1. For each hour, divide distribution into N parts of equal probability (N = sample size)
2. Draw a random sample from each part
3. Shuffle hourly sets
4. Create random vector from hourly sets

Results | Variance reduction





Influence of Multiprocessing



Electric vehicle

Characteristics:

$E_{\sigma_s}^{M} = 38kWh$ (Maximum storage level)

$E_{\sigma_s}^{m} = 0kWh$ (Minimum storage level)

$p_{\sigma_s}^{w} = 11kW$ (Maximum withdrawal power)

$p_{\sigma_s}^{i} = 11kW$ (Maximum charging power)

Constraints:

$$E_{\sigma_s}^{m} \leq E_{\sigma_s}[h] \leq E_{\sigma_s}^{M}$$

$$E_{\sigma_s}[h] = E_{\sigma_s}[h-1] - P_{\sigma_s}^{net}[h] \cdot 1h$$

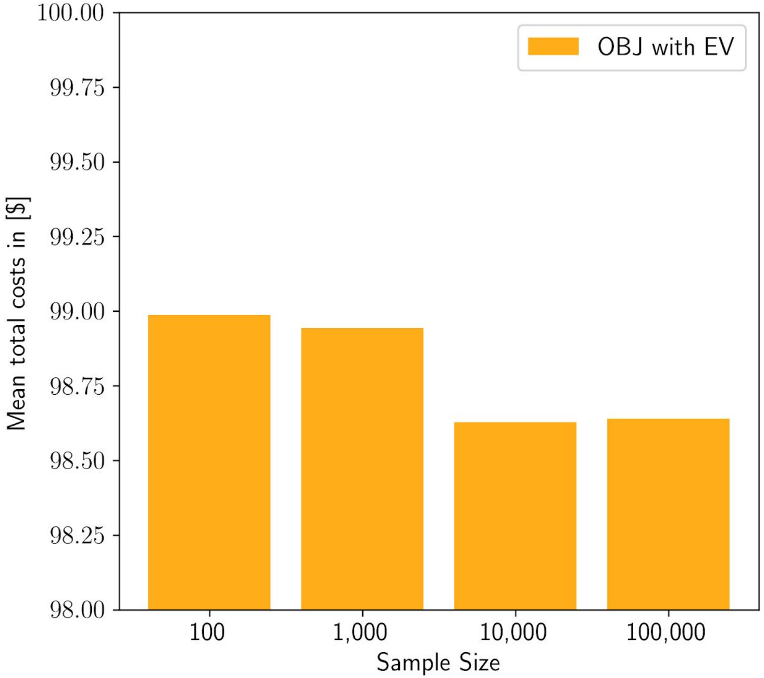
$$-p_{\sigma_s}^{i} \leq P_{\sigma_s}^{net} \leq p_{\sigma_s}^{w}$$

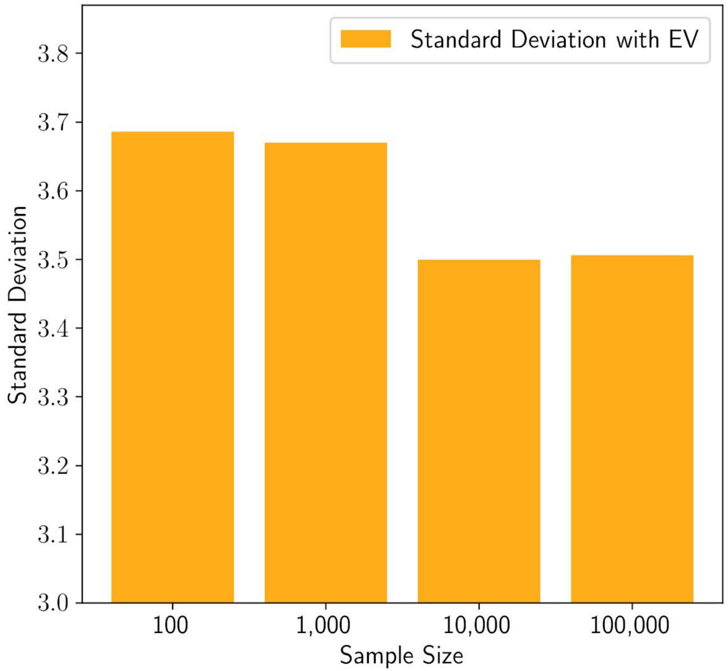
$$E_{\sigma_s}[0] = 0.2 \cdot E_{\sigma_s}^{M} = 7.6kWh$$

$$E_{\sigma_s}[24] = 0.8 \cdot E_{\sigma_s}^{M} = 30.4kWh$$

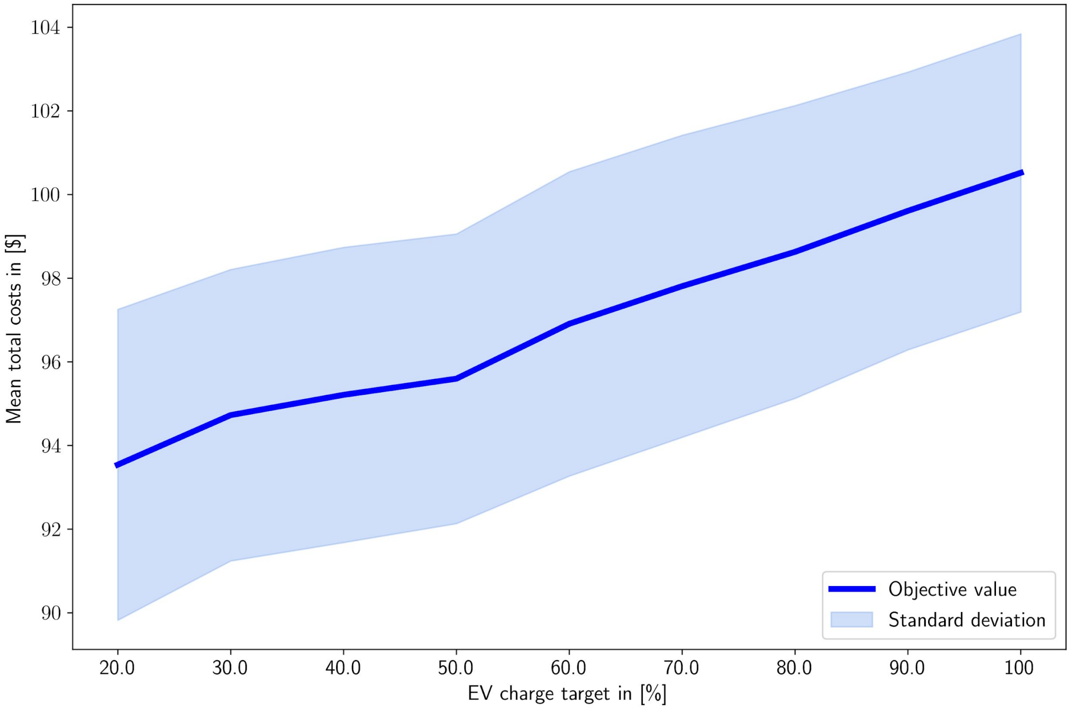
$E_{\sigma_s}[h]$: Energy storage level in hour h $P_{\sigma_s}^{net}[h]$: Net power injection in hour h

Electric vehicle | Results





Electric vehicle | Sensitivity



References

Homem-de-Mello & Bayraksan (2016). *Scenario Generation and Sampling Methods.* [PDF Presentation Slides]. Accessible via https://www.youtube.com/watch?v=RkUdWL_3KLA

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

Thanks for your attention

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