TU Delft

Variance in Steady-State Simulation Optimization:

Key Challenges and Algorithms

Group 9

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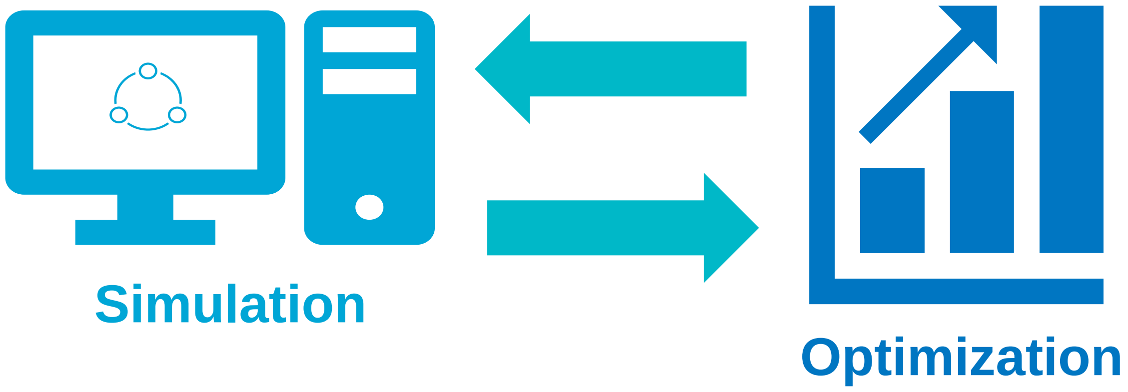
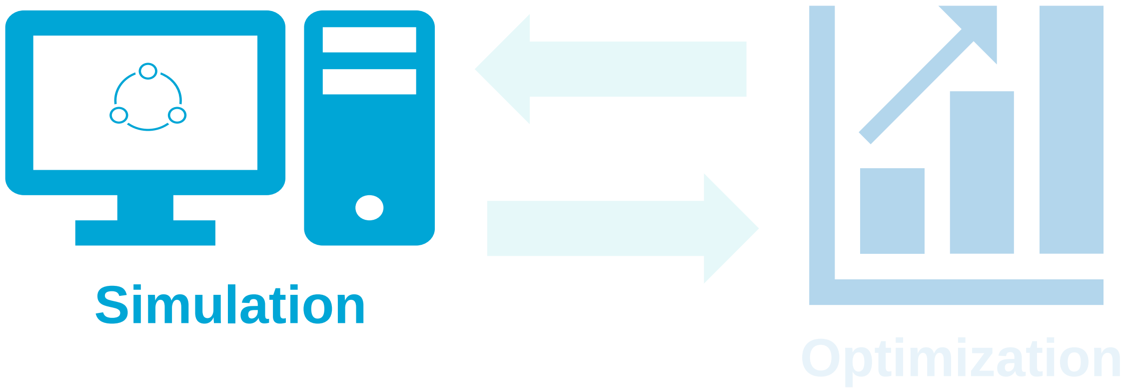
Simulation Optimization

- Model complex (stochastic) systems
- Optimize these models
- Support decision making
- Explore large solution spaces



Simulation

- Simulate until steady state
- Simulation variability (finite run time)
- Parameter variability (input data)

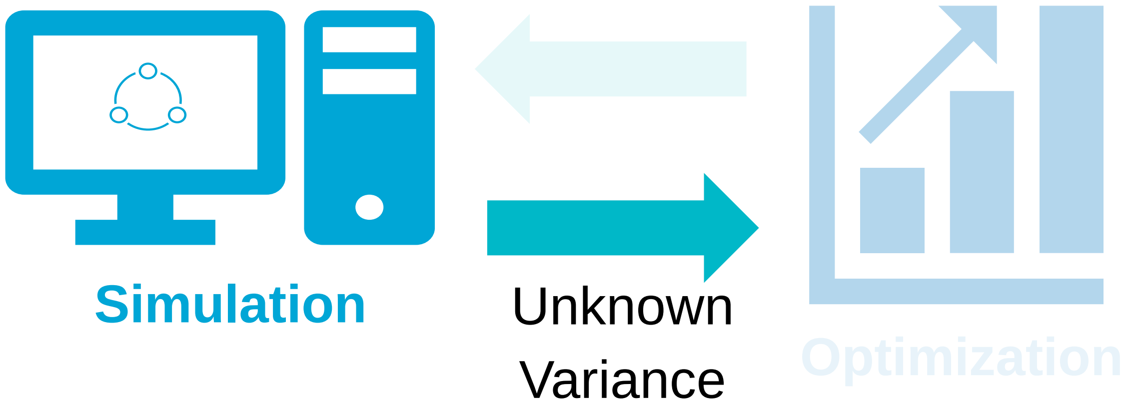


Problem statement

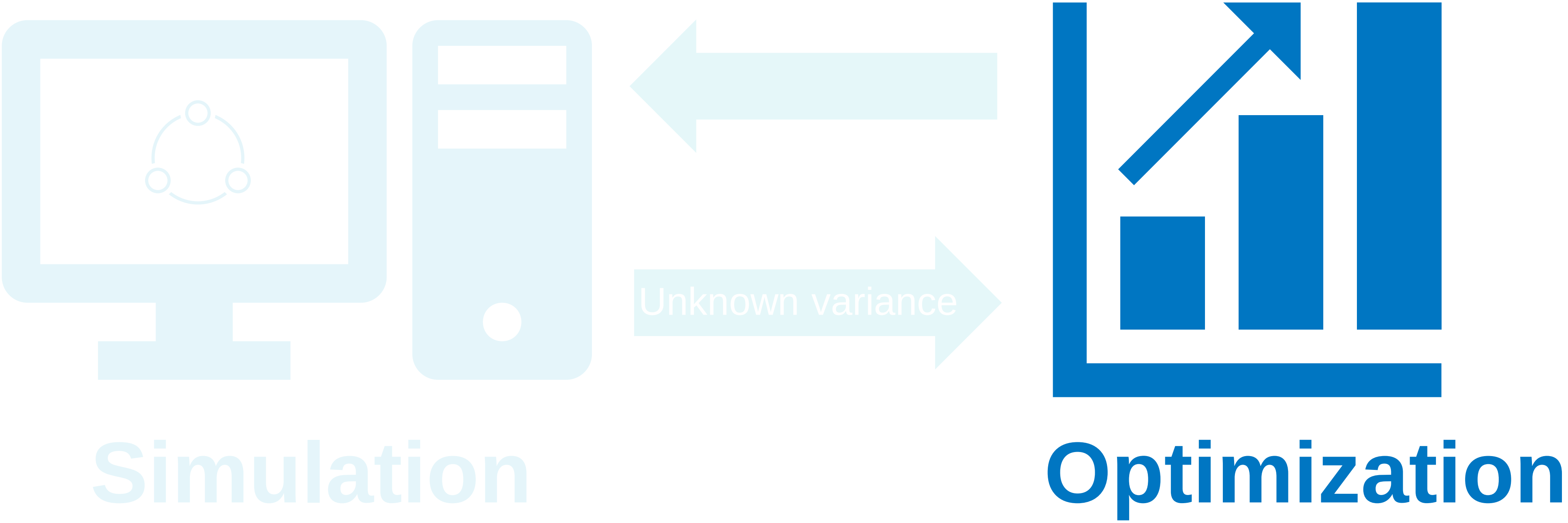
- Variability in Simulation **output**, thus variability in optimizer **input**

- Variance is unknown (late ‘60)

- Conway: batches

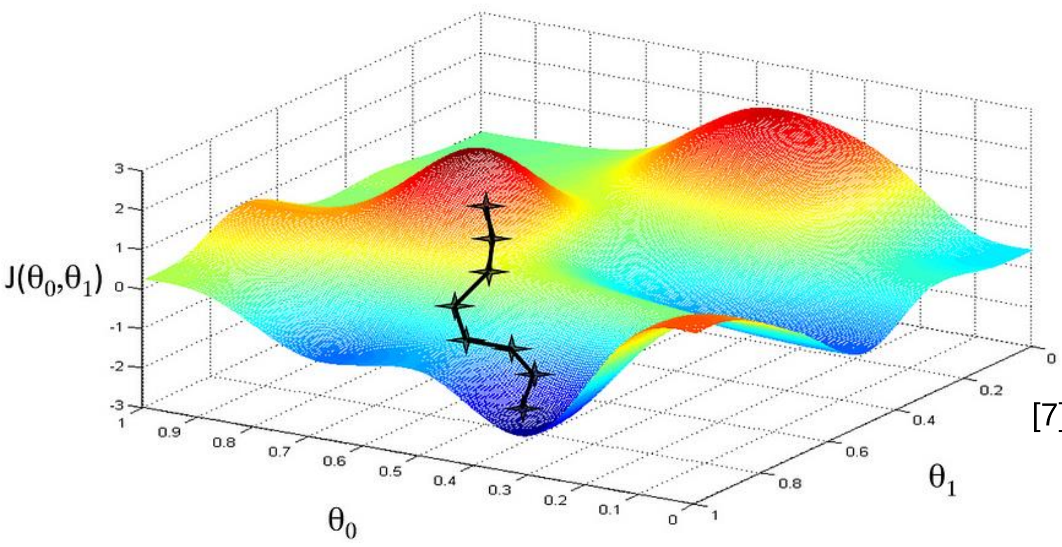


Optimization



Stochasticity in Optimization Models

Two classes of classification methods:



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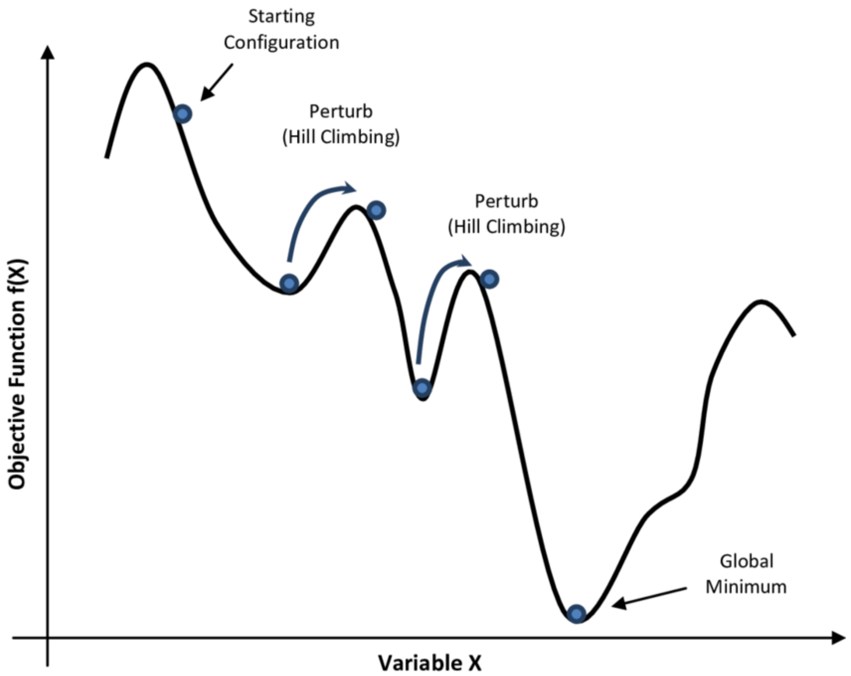

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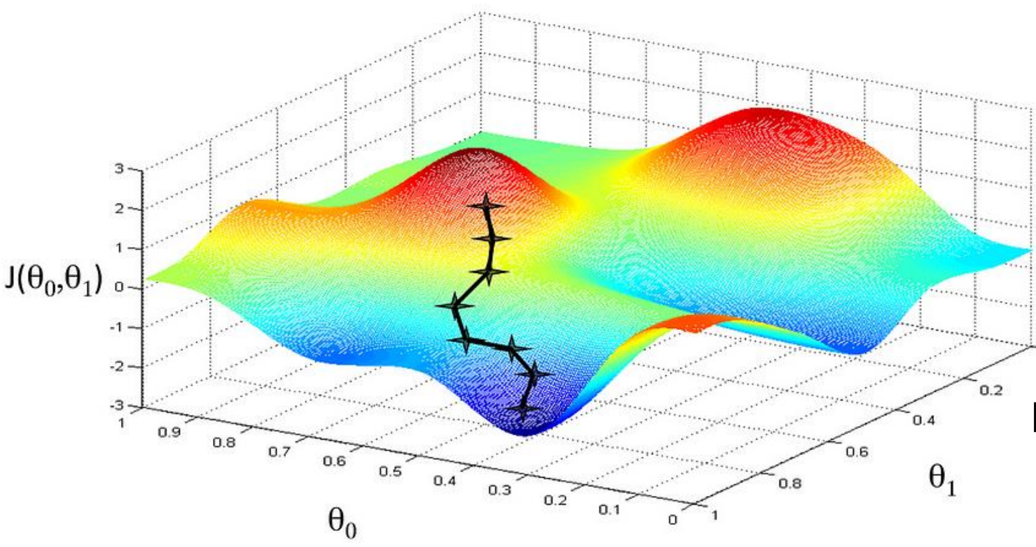
Mathematical Optimization

Approximate Algorithms

Stochasticity in Optimization Models



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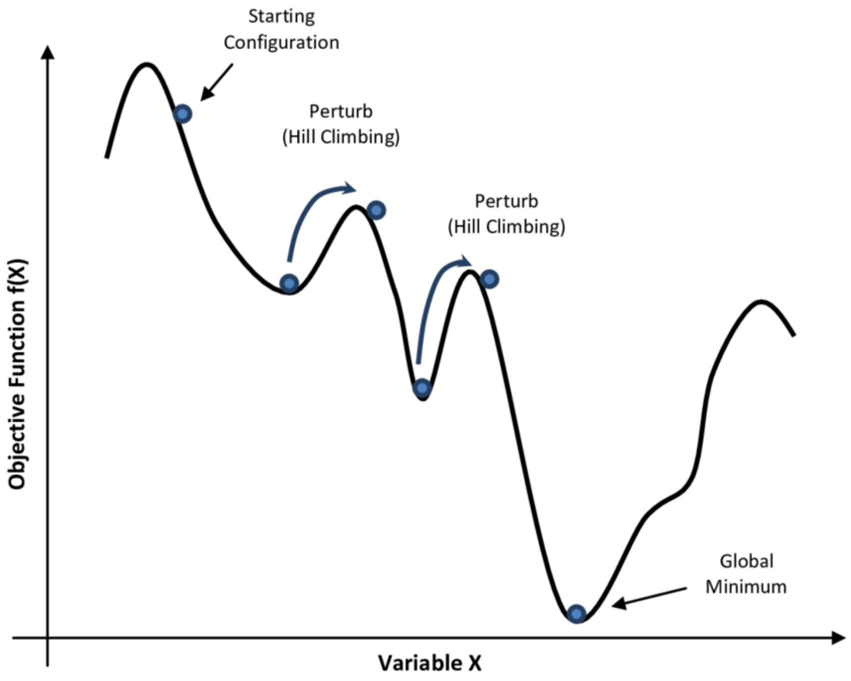
Mathematical Optimization

- Combination of techniques and methods for finding optimum within a set of constraints [1]
- Examples are **linear optimization** and **non-linear optimization** [1]
- **Use cases** for simulation-based optimization:
  - Sensitivity analysis [2]
  - Validation of starting points & solutions [3]
- **Problems** through stochasticity:
  - Need of precise values

Stochasticity in Optimization Models

- Focus on quick good solutions rather than finding optimal solutions
- Examples are **heuristics** and **metaheuristics** [4]
- **Use cases** for simulation-based optimization:
  - Comparison of different strategies [5]
  - Validation of solutions [5]
- **Problems** through stochasticity:
  - Interpretation of simulation results becomes more difficult



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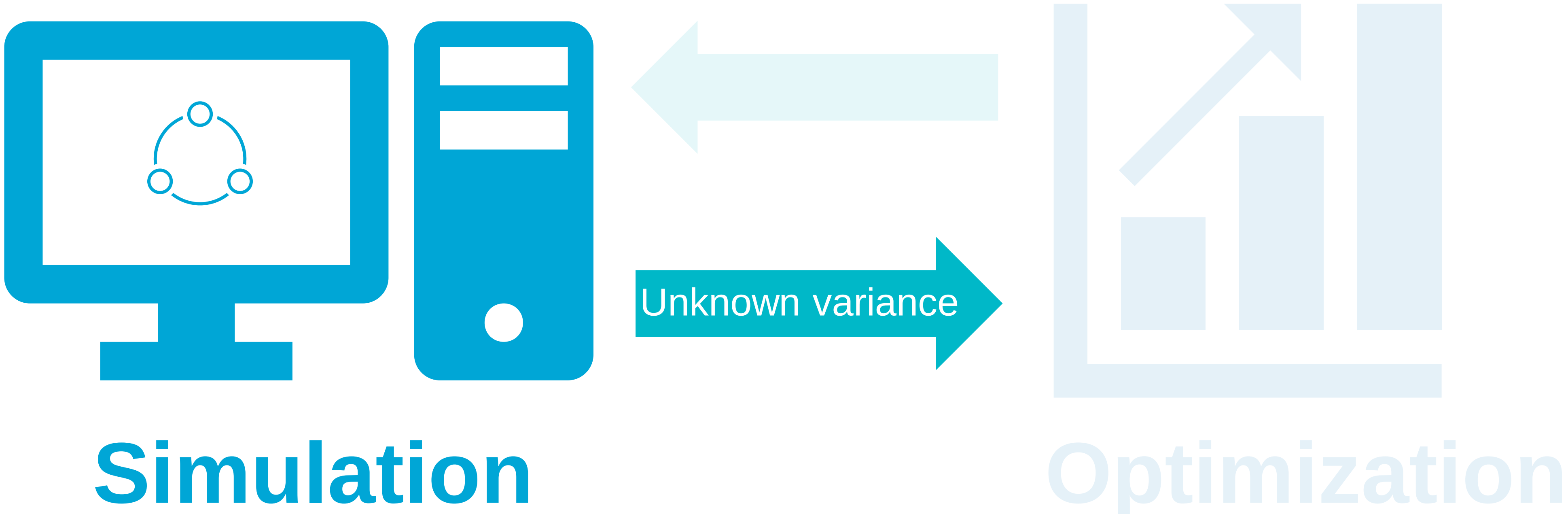
Approximate Algorithms

Variance in Simulation output



Asymptotic Normality Theory

Predictable distribution of simulation averages

Based on Central Limit Theorem
Assumes finite variance
Assumes not fat tailed distribution
Assumes large sample size
Results in confidence intervals
Uses Gaussian distribution

Bootstrapping

Resampling to estimate variability without strong assumptions

Based on observed data
No assumptions
Less simulation runs needed
More computation needed

Direct Two-Point Method

Simple variance estimation through independent runs

Based on difference of two points
Assumes rough spread around the mean
Quick and simple
Not robust

Possible combination with optimization models

Mathematical optimization

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Asymptotic Normality Theory

+ Asymptotic Normality Theory enables precise values

− High computational time for both simulation & optimization

Approximate algorithms

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Bootstrapping

+ Better understanding of distribution

Metrics like VaR & CVaR can ensure robust performance [8]

Thank you for your attention!

References

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