

# Stochastically Constrained Optimization via Simulation

Seong-Hee Kim

Georgia Institute of Technology

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# Problem

## Notation

- ▶  $\mathbf{x}$ : a solution with discrete decision variables.
- ▶  $\Theta$ : the set of possible solutions  $\mathbf{x}$ .

Want to find:

$$\begin{aligned} \operatorname{argmin}_{\mathbf{x} \in \Theta} g(\mathbf{x}) &= \mathbf{E}_{\mathbf{x}}[Y(\mathbf{x})] \\ \text{subject to } h(\mathbf{x}) &= \mathbf{E}_{\mathbf{x}}[C(\mathbf{x})] \geq q \end{aligned}$$

- ▶  $g(\mathbf{x})$  and  $h(\mathbf{x})$  are estimated only through simulation.
- ▶ Existing OvS algorithms are designed without consideration for stochastic constraints.

## Set Up

- ▶ One replication generates one observation  $Y(\mathbf{x})$  and  $C(\mathbf{x})$ .
- ▶ At search iteration  $k$ , a number of solutions are generated and a number of replications are made for each generated solution.
- ▶ Let  $n_k(\mathbf{x})$  represent the total number of replications made up to search iteration  $k$  for  $\mathbf{x}$ .
- ▶ Let  $v_k(\mathbf{x})$  represent the number of visits to  $\mathbf{x}$  made up to search iteration  $k$ .

- ▶  $\widehat{g}_{v_k}(\mathbf{x})$  and  $\widehat{h}_{v_k}(\mathbf{x})$  are sample averages of all available observations up to  $v_k$  visits (i.e., sample averages of  $n_k$  observations).
- ▶ Define the penalty factor,  $\lambda_{v_k}(\mathbf{x})$  as

$$\lambda_{v_k}(\mathbf{x}) = \begin{cases} \lambda_{v_k-1}(\mathbf{x}) \times \theta_1, & \text{if } \widehat{h}_{v_k}(\mathbf{x}) \geq q; \\ \lambda_{v_k-1}(\mathbf{x}) \times \theta_2, & \text{if } \widehat{h}_{v_k}(\mathbf{x}) < q, \end{cases}$$

where  $\lambda_0(\mathbf{x}) = 1$  for all  $\mathbf{x} \in \Theta$ ,  $0 < \theta_1 < 1$ , and  $\theta_2 > 1$ .

## Penalized Objective

The penalized objective at search iteration  $k$  is defined as

$$Z_{v_k}(\mathbf{x}) = \widehat{g}_{v_k}(\mathbf{x}) + \lambda_{v_k}(\mathbf{x}) \times \max\{0, q - \widehat{h}_{k_v}(\mathbf{x})\} \times P,$$

where  $P$  is a penalty constant and can be one.

Why does it work?

- ▶ If an OvS algorithms satisfy  $v_k(\mathbf{x}) \rightarrow \infty$  and  $n_k(\mathbf{x}) \rightarrow \infty$  as  $k \rightarrow \infty$ , then

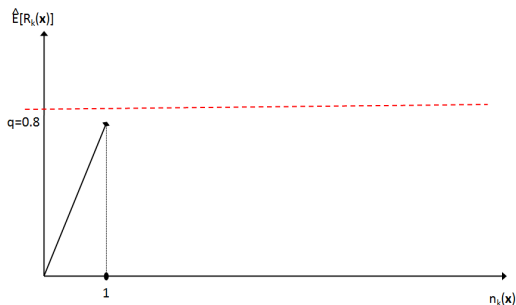
$$\begin{aligned} Z_{v_k}(\mathbf{x}) &\rightarrow g(\mathbf{x}) \text{ w.p. 1, if } \mathbf{x} \text{ is strictly feasible; and} \\ Z_{k_k}(\mathbf{x}) &\rightarrow \infty \text{ w.p. 1, otherwise.} \end{aligned}$$

## Example

Constraint: Contaminant spill detection reliability  $h(\mathbf{x}) \geq 0.8$ .

Consider a solution with  $h(\mathbf{x}) = 0.65$  and set  $P = 1$ .

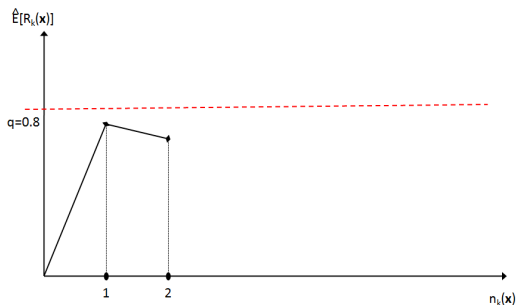
- ▶ Observe  $\hat{h}_1(\mathbf{x}) = 0.75$  ( $\theta_1 = 0.1$  and  $\theta_2 = 10$ ).
- ▶  $\lambda_1(\mathbf{x}) = \lambda_0(\mathbf{x}) \times \theta_2 = 1 \times 10 = 10$ .
- ▶  $\lambda_1(\mathbf{x}) \times \max\{0, q - \hat{h}_1(\mathbf{x})\} = 10 \times \max\{0, 0.10\} = 1$ .



## Example

Constraint: Contaminant spill detection reliability  $h(\mathbf{x}) \geq 0.8$ .  
Consider a solution with  $h(\mathbf{x}) = 0.65$  and set  $P = 1$ .

- ▶ Observe  $\hat{h}_2(\mathbf{x}) = 0.70$  ( $\theta_1 = 0.1$  and  $\theta_2 = 10$ ).
- ▶  $\lambda_2(\mathbf{x}) = \lambda_1(\mathbf{x}) \times \theta_2 = 10 \times 10 = 100$ .
- ▶  $\lambda_2(\mathbf{x}) \times \max\{0, q - \hat{h}_2(\mathbf{x})\} = 100 \times \max\{0, 0.10\} = 10$ .

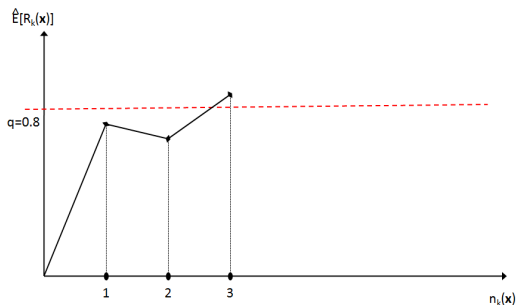


## Example

Constraint: Contaminant spill detection reliability  $h(\mathbf{x}) \geq 0.8$ .

Consider a solution with  $h(\mathbf{x}) = 0.65$  and set  $P = 1$ .

- ▶ Observe  $\hat{h}_3(\mathbf{x}) = 0.84$  ( $\theta_1 = 0.1$  and  $\theta_2 = 10$ ).
- ▶  $\lambda_3(\mathbf{x}) = \lambda_2(\mathbf{x}) \times \theta_1 = 100 \times 0.1 = 10$ .
- ▶  $\lambda_3(\mathbf{x}) \times \max\{0, q - \hat{h}_3(\mathbf{x})\} = 10 \times \max\{0, -0.04\} = 0$ .

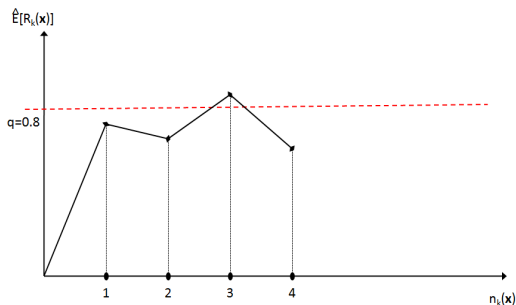




## Example

Constraint: Contaminant spill detection reliability  $h(\mathbf{x}) \geq 0.8$ .  
Consider a solution with  $h(\mathbf{x}) = 0.65$  and set  $P = 1$ .

- ▶ Observe  $\hat{h}_4(\mathbf{x}) = 0.65$  ( $\theta_1 = 0.1$  and  $\theta_2 = 10$ ).
- ▶  $\lambda_4(\mathbf{x}) = \lambda_3(\mathbf{x}) \times \theta_2 = 10 \times 10 = 100$ .
- ▶  $\lambda_4(\mathbf{x}) \times \max\{0, q - \hat{h}_4(\mathbf{x})\} = 100 \times \max\{0, 0.15\} = 15$ .

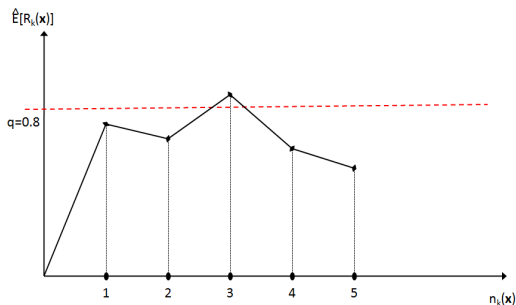


## Example

Constraint: Contaminant spill detection reliability  $h(\mathbf{x}) \geq 0.8$ .

Consider a solution with  $h(\mathbf{x}) = 0.65$  and set  $P = 1$ .

- ▶ Observe  $\hat{h}_5(\mathbf{x}) = 0.60$  ( $\theta_1 = 0.1$  and  $\theta_2 = 10$ ).
- ▶  $\lambda_5(\mathbf{x}) = \lambda_4(\mathbf{x}) \times \theta_2 = 100 \times 10 = 1000$ .
- ▶  $\lambda_5(\mathbf{x}) \times \max\{0, q - \hat{h}_5(\mathbf{x})\} = 1000 \times \max\{0, 0.20\} = 200$ .

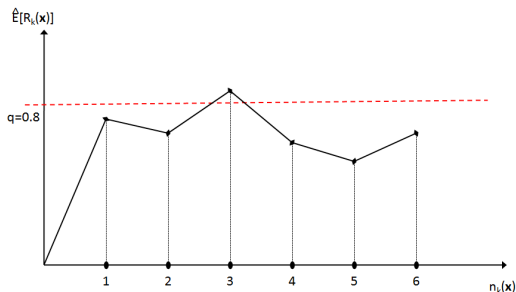


## Example

Constraint: Contaminant spill detection reliability  $h(\mathbf{x}) \geq 0.8$ .

Consider a solution with  $h(\mathbf{x}) = 0.65$  and set  $P = 1$ .

- ▶ Observe  $\hat{h}_6(\mathbf{x}) = 0.65$  ( $\theta_1 = 0.1$  and  $\theta_2 = 10$ ).
- ▶  $\lambda_6(\mathbf{x}) = \lambda_5(\mathbf{x}) \times \theta_2 = 1000 \times 10 = 10000$ .
- ▶  $\lambda_6(\mathbf{x}) \times \max\{0, q - \hat{h}_6(\mathbf{x})\} = 10000 \times \max\{0, 0.15\} = 1500$ .



## Multiple Constraints

$$\begin{aligned} \operatorname{argmin}_{\mathbf{x} \in \Theta} g(\mathbf{x}) &= \mathbf{E}_{\mathbf{x}}[Y(\mathbf{x})], \\ \text{subject to } h^i(\mathbf{x}) &= \mathbf{E}_{\mathbf{x}}[C_i(\mathbf{x})] \geq q_i \quad i = 1, 2, \dots, s \end{aligned}$$

$$\lambda_{v_k}^i(\mathbf{x}) = \begin{cases} \lambda_{v_k-1}^i(\mathbf{x}) \times \theta_1, & \text{if } \hat{h}_{v_k}^i(\mathbf{x}) \geq q^i; \\ \lambda_{v_k-1}^i(\mathbf{x}) \times \theta_2, & \text{if } \hat{h}_{v_k}^i(\mathbf{x}) < q^i, \end{cases}$$

where  $\lambda_0^i(\mathbf{x}) = 1$  for all  $\mathbf{x} \in \Theta$ ,  $0 < \theta_1 < 1$ , and  $\theta_2 > 1$ .

$$Z_{v_k}(\mathbf{x}) = \hat{g}_{v_k}(\mathbf{x}) + \sum_{i=1}^s \lambda_{v_k}^i(\mathbf{x}) \times \max\{0, q - \hat{h}_{v_k}^i(\mathbf{x})\} \times P^i.$$

## Issues

- ▶ What if  $h^i(\mathbf{x}) = q_i$ ?
- ▶ Choice of  $\theta_1$  and  $\theta_2$ : Make it as a function of  $n$ ?
  - ▶  $0 < \theta_1 < 1$ : Start with a large number then decrease it as  $n$  increases.
  - ▶  $\theta_2 > 1$ : Start with a small number and increase it as  $n$  increases.
- ▶ Give some tolerance for feasibility decision?
  - ▶ feasible if  $\widehat{h}_{v_k}(\mathbf{x}) \geq q - \epsilon$ ; and
  - ▶ infeasible if  $\widehat{h}_{v_k}(\mathbf{x}) \leq q + \epsilon$ .
- ▶ Incorporate constrained ranking and selection?
- ▶ Other issues?