

MEM6804 Modeling and Simulation for Logistics & Supply Chain



物流与供应链建模与仿真

Theory Analysis

Lecture 10: Output Analysis III: Optimization

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- **Optimization via Simulation (OvS)**, or, simply called Simulation Optimization (SO):

$$\min_{\mathbf{x} \in \mathcal{X}} g(\mathbf{x}) := \mathbb{E}[G(\mathbf{x}, \xi)],$$

where $\mathcal{X} \subset \mathbb{R}^d$ is the feasible set, and $g : \mathcal{X} \rightarrow \mathbb{R}$ is a deterministic function whose values can only be evaluated with noisy observations.

- Given \mathbf{x} , $G(\mathbf{x}, \xi)$ is a random variable (the randomness is from ξ), and the distribution of $G(\mathbf{x}, \xi)$ is unknown.
- Given \mathbf{x} , realizations of $G(\mathbf{x}, \xi)$ can be observed by running simulation, or more generally, taking samples.

- OvS Problem can be classified into two types according to whether the explicit form of $G(\boldsymbol{x}, \xi)$ is available.
- **White-box**: The explicit form of $G(\boldsymbol{x}, \xi)$ is available.
 - Example: $G(x, \xi) = \sin((x - \xi)^2)$, where the distribution of ξ is unknown.
- **Black-box**: The explicit form of $G(\boldsymbol{x}, \xi)$ is not available and it is embedded in a simulation model.
 - Example: Let $G(\boldsymbol{x}, \xi)$ be the waiting time of a customer in a complex queueing network, where \boldsymbol{x} represents the configuration parameters.

- OvS Problem can be classified into three types according to the feasible set \mathcal{X} .
- **Ranking and selection (R&S)**: \mathcal{X} is a set of relatively small number of (discrete) solutions.
- **Discrete OvS (DOvS)**: \mathcal{X} is a discrete set, with huge or even countably infinite number of solutions.
 - One can also view R&S problem as a special type of DOvS problem.
- **Continuous OvS (COvS)**: \mathcal{X} is a continuous set, hence there exists uncountably infinite number of solutions.

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- For white-box OvS problems, we can use the sample average approximation.
- Of course, those algorithms designed for black-box OvS problems can also be applied to white-box OvS problems.

- Suppose that we have an iid sample $\{\xi_1, \dots, \xi_n\}$ of ξ .
- To solve $\min_{\mathbf{x} \in \mathcal{X}} g(\mathbf{x}) := \mathbb{E}[G(\mathbf{x}, \xi)]$, we try to solve

$$\min_{\mathbf{x} \in \mathcal{X}} \hat{g}_n(\mathbf{x}) := \frac{1}{n} \sum_{i=1}^n G(\mathbf{x}, \xi_i),$$

with any suitable deterministic optimization algorithm (after $\{\xi_1, \dots, \xi_n\}$ is realized).

- This method is called Sample Average Approximation (SAA); see [Kim et al. \(2015\)](#) for a review.
- Clearly, for finite n , $\inf_{\mathbf{x} \in \mathcal{X}} \hat{g}_n(\mathbf{x})$ is a random variable (before $\{\xi_1, \dots, \xi_n\}$ is realized), and it is not strictly equal to $\min_{\mathbf{x} \in \mathcal{X}} g(\mathbf{x})$.

- Indeed, one can prove that

$$\mathbb{E} \left[\inf_{\mathbf{x} \in \mathcal{X}} \hat{g}_n(\mathbf{x}) \right] \leq \min_{\mathbf{x} \in \mathcal{X}} g(\mathbf{x}).$$

Proof. For any $\mathbf{y} \in \mathcal{X}$,

$$\inf_{\mathbf{x} \in \mathcal{X}} \hat{g}_n(\mathbf{x}) \leq \hat{g}_n(\mathbf{y}) \implies \mathbb{E} \left[\inf_{\mathbf{x} \in \mathcal{X}} \hat{g}_n(\mathbf{x}) \right] \leq \mathbb{E}[\hat{g}_n(\mathbf{y})] = g(\mathbf{y}).$$

Minimizing the right-hand side over all $\mathbf{y} \in \mathcal{X}$ completes the proof. ■

- Moreover, it can also be shown that

$$\mathbb{E} \left[\inf_{\mathbf{x} \in \mathcal{X}} \hat{g}_n(\mathbf{x}) \right] \leq \mathbb{E} \left[\inf_{\mathbf{x} \in \mathcal{X}} \hat{g}_{n+1}(\mathbf{x}) \right] \leq \min_{\mathbf{x} \in \mathcal{X}} g(\mathbf{x}).$$

(Prove it as an exercise)

- What can we say if we continuously increase sample size n ?
- It will be **reassuring** if we know that the obtained solution will be closer and closer to the true solution, as we increase sample size n .
- Formally, we are seeking for a **convergence** guarantee for SAA method.

- For set $\mathcal{A} \subset \mathbb{R}^d$, the distance from $\mathbf{x} \in \mathbb{R}^d$ to \mathcal{A} is defined as

$$\text{dist}(\mathbf{x}, \mathcal{A}) := \inf_{\mathbf{y} \in \mathcal{A}} \|\mathbf{x} - \mathbf{y}\|,$$

where $\|\cdot\|$ denotes the Euclidean distance.

- For sets $\mathcal{A}, \mathcal{B} \subset \mathbb{R}^d$, the deviation from \mathcal{A} to \mathcal{B} is defined as

$$D(\mathcal{A}, \mathcal{B}) := \sup_{\mathbf{x} \in \mathcal{A}} \text{dist}(\mathbf{x}, \mathcal{B}).$$

- Let

$$\mathcal{S} := \underset{\mathbf{x} \in \mathcal{X}}{\text{argmin}} g(\mathbf{x}),$$

$$\widehat{\mathcal{S}}_n := \underset{\mathbf{x} \in \mathcal{X}}{\text{argmin}} \widehat{g}_n(\mathbf{x}).$$

Convergence of SAA (Theorem 5.3 of Shapiro et al. (2009))

Suppose that

- ① \mathcal{X} is a compact set;
- ② $g(x)$ is finite valued and continuous on \mathcal{X} ;
- ③ $\mathbb{P}\{\widehat{g}_n(x) \rightarrow g(x) \text{ uniformly in } x \in \mathcal{X}\} = 1$;
- ④ $\mathbb{P}\{\widehat{\mathcal{S}}_n \text{ is nonempty for } n \text{ large enough}\} = 1$;

Then, as $n \rightarrow \infty$,

$$\min_{x \in \mathcal{X}} \widehat{g}_n(x) \xrightarrow{a.s.} \min_{x \in \mathcal{X}} g(x), \text{ and } D(\widehat{\mathcal{S}}_n, \mathcal{S}) \xrightarrow{a.s.} 0.$$

Besides, if $\mathcal{S} = \{x^*\}$ is a singleton, then for any $\widehat{x}_n \in \widehat{\mathcal{S}}_n$,

$$\widehat{x}_n \xrightarrow{a.s.} x^*, \text{ as } n \rightarrow \infty.$$

- **How fast** does the SAA solution converge to the true solution?
- Formally, it's known as the **rate of convergence**.
- Under certain regularity conditions, one may show that

$$\left| \min_{\mathbf{x} \in \mathcal{X}} \widehat{g}_n(\mathbf{x}) - \min_{\mathbf{x} \in \mathcal{X}} g(\mathbf{x}) \right| = O_p(n^{-1/2}),$$

and given $\mathcal{S} = \{\mathbf{x}^*\}$ is a singleton,

$$\|\widehat{\mathbf{x}}_n - \mathbf{x}^*\| = O_p(n^{-1/2}).$$

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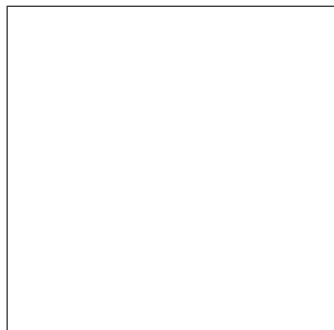
- Main types of algorithms for black-box COvS problems:
 - random search; see [Andradóttir \(2015\)](#) for a review;
 - stochastic approximation; see [Chau and Fu \(2015\)](#) for a review;
 - surrogate-based methods; see [Hong and Zhang \(2021\)](#) for a review.
- Stochastic Approximation (SA) was proposed by [Robbins and Monro \(1951\)](#) and [Kiefer and Wolfowitz \(1952\)](#).
- SA can be viewed as a stochastic version of the gradient descent (or called steepest descent) algorithm, so it is also called stochastic gradient descent.

- Gradient descent is a first-order iterative optimization algorithm for finding a local minimum of a differentiable (deterministic) function:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \gamma \nabla g(\mathbf{x}_k),$$

where $\nabla g(\mathbf{x})$ is the gradient and $\gamma > 0$ is the step size.

- If the minimization problem is constrained, say the feasible set $\mathcal{X} \subset \mathbb{R}^d$ is convex and compact, one can easily add a projection $\Pi_{\mathcal{X}}(\mathbf{x})$ mapping $\mathbf{x} \notin \mathcal{X}$ back into \mathcal{X} .



- The value of the step size γ is allowed to change at every iteration, and with proper choice, convergence to a local minimizer (say, \mathbf{x}^*) can be guaranteed, i.e., $\mathbf{x}_k \rightarrow \mathbf{x}^*$.
- Under certain regularity conditions, one can show that $|g(\mathbf{x}_k) - g(\mathbf{x}^*)| = O(k^{-1})$ for unconstrained problem with constant γ .

- SA as a stochastic version of the gradient ascent:

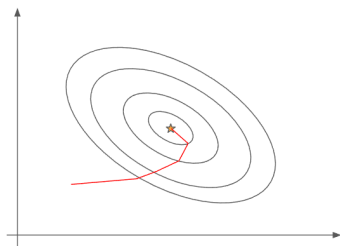
$$\mathbf{X}_{k+1} = \Pi_{\mathcal{X}} \left(\mathbf{X}_k - a_k \widehat{\nabla} g(\mathbf{X}_k) \right),$$

where $\Pi_{\mathcal{X}}$ is the projection, $\{a_k\}_{k \geq 1}$ is a deterministic positive sequence for step size, and $\widehat{\nabla} g(\mathbf{x})$ is an estimator of the gradient $\nabla g(\mathbf{x})$.

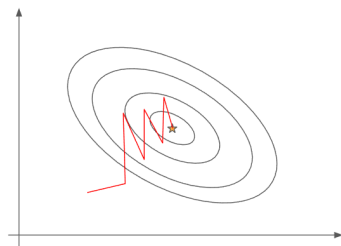
- In some simulation experiments, unbiased $\widehat{\nabla} g(\mathbf{x})$ is available,[†] then it is the Robbins-Monro (RM) type SA (Robbins and Monro 1951).
- Otherwise, $\widehat{\nabla} g(\mathbf{x})$ needs to be constructed with certain indirect method (thus biased), then it is the Kiefer-Wolfowitz (KW) type SA (Kiefer and Wolfowitz (1952)).

[†]When we observe $G(\mathbf{x}, \xi)$, we will also observe $\widehat{\nabla} g(\mathbf{x}, \xi)$ at the same time such that $\mathbb{E}[\widehat{\nabla} g(\mathbf{x}, \xi)] = \nabla g(\mathbf{x})$.

- Gradient descent vs SA (i.e., stochastic gradient descent):



Gradient Descent



Stochastic Gradient Descent



- Construct $\widehat{\nabla}g(\mathbf{X}_k)$ via symmetric (or central) finite difference:

$$\widehat{\nabla}g(\mathbf{X}_k) := (g_1(\mathbf{X}_k), \dots, g_d(\mathbf{X}_k))^{\top},$$

where

$$g_i(\mathbf{X}_k) := \frac{G(\mathbf{X}_k + c_k \mathbf{e}_i) - G(\mathbf{X}_k - c_k \mathbf{e}_i)}{2c_k},$$

\mathbf{e}_i denotes a $d \times 1$ vector whose i th element is one and other elements are all zeros, $i = 1, \dots, d$, and $\{c_k\}_{k \geq 1}$ is a deterministic positive sequence.

- It requires $2d$ **additional** simulation runs (samples) to compute $\widehat{\nabla}g(\mathbf{X}_k)$.

- Let \mathcal{M} denote the set of local optimal solutions:

$$\mathcal{M} := \left\{ \mathbf{x} \in \mathcal{X} : g(\mathbf{x}) \leq \min_{\mathbf{y} \in \mathcal{B}(\mathbf{x})} g(\mathbf{y}) \right\},$$

where $\mathcal{B}(\mathbf{x}) \subset \mathcal{X}$ denotes a neighborhood of $\mathbf{x} \in \mathcal{X}$.

Local Convergence of SA (Theorem 3 of Blum (1954))

Suppose that

- 1 $g(x)$ satisfies certain regularity conditions;
- 2 $\text{Var}(G(\mathbf{x}, \xi)) \leq \sigma^2 < \infty$;
- 3 $\lim_{k \rightarrow \infty} c_k = 0$, $\sum_{k=1}^{\infty} a_k = \infty$, $\sum_{k=1}^{\infty} a_k c_k < \infty$, and $\sum_{k=1}^{\infty} a_k^2 c_k^{-2} < \infty$.

Then, for KW type SA with symmetric difference gradient estimator, $\text{dist}(\mathbf{X}_k, \mathcal{M}) \xrightarrow{a.s.} 0$ as $k \rightarrow \infty$.

- Under certain conditions, for $\mathbf{x}^* \in \mathcal{M}$ such that $\mathbf{X}_k \xrightarrow{a.s.} \mathbf{x}^*$, RM type SA can reach $O_p(k^{-1/2})$ rate of convergence, i.e.,

$$\|\mathbf{X}_k - \mathbf{x}^*\| = O_p(k^{-1/2}),$$

while KW type SA can reach $O_p(k^{-1/3})$ rate of convergence.

- Note that the above order is in terms of the iteration number k , rather than the number of simulation runs (sample size).
- If in terms of the sample size n , the rate of convergence of KW type SA is $O_p((n/d)^{-1/3})$, which depends on the dimensionality d .

- Simultaneous perturbation stochastic approximation (SPSA):

$$\widehat{\nabla} g(\mathbf{X}_k) := (g_1(\mathbf{X}_k), \dots, g_d(\mathbf{X}_k))^\top,$$

where

$$g_i(\mathbf{X}_k) := \frac{G(\mathbf{X}_k + c_k \mathbf{B}_k) - G(\mathbf{X}_k - c_k \mathbf{B}_k)}{2c_k B_{k,i}},$$

$\mathbf{B}_k := (B_{k,1}, \dots, B_{k,d})^\top$, and $B_{k,i} = 1$ or -1 with probability $1/2$.

- It requires only 2 **additional** simulation runs (samples) to compute $\widehat{\nabla} g(\mathbf{X}_k)$, no matter what d is.
- SPSA can reach $O_p(n^{-1/3})$ rate of convergence in terms of the sample size n .

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- Many black-box DOvS algorithms are based on random search; see [Hong et al. \(2015\)](#) for a review.
- The framework of random search:
 - **Initialization:** Arbitrarily choose $x_0^* \in \mathcal{X}$; set the information set (that keeps visited solutions and their corresponding observations) \mathcal{F}_0 ; set iteration index $k = 0$.
 - **At Iteration k :**
 - **Sampling:** Choose the estimation set $\mathcal{E} \subset \mathcal{X}$ (that contains solutions at which simulation will be run); some or all of the solutions in \mathcal{E} are randomly sampled from \mathcal{X} with distribution determined by information \mathcal{F}_k .
 - **Evaluation:** For each $x \in \mathcal{E}$, spend simulation effort according to certain rule determined by \mathcal{F}_k and \mathcal{E} .
 - **Updating:** Update \mathcal{F}_{k+1} ; choose some x_{k+1}^* as the current best solution based on certain estimator; set $k \leftarrow k + 1$.

- The simulated annealing algorithm dates back to the pioneering work by [Metropolis et al. \(1953\)](#).
 - It studied how in the physical annealing process, particles of a solid arrange themselves into thermal equilibrium at a given temperature.
- A large body of literature has developed the simulated annealing algorithm to solve deterministic global optimization problems over **finite** set; important works include [Kirkpatrick et al. \(1983\)](#), [Mitra et al. \(1986\)](#), [Hajek \(1988\)](#), etc.
- Later, the simulated annealing was extended to solve black-box DOvS problems over **finite** set; important works include [Bulgak and Sander \(1988\)](#), [Gelfand and Mitter \(1989\)](#), [Alrefaei and Andradóttir \(1999\)](#), etc.

- Let $\mathcal{B}(x) \subset \mathcal{X}$ denote a neighborhood[†] of $x \in \mathcal{X}$.
- $\mathcal{B}(x)$ is carefully desined such that, for any $x, y \in \mathcal{X}$, y is reachable from x .
 - That is, there exists a finite sequence $x = x_0, x_1, \dots, x_\ell = y$ such that $x_{i+1} \in \mathcal{B}(x_i)$, $i = 0, 1, \dots, \ell - 1$.
- Define transition probability $R(x, y)$, where $R: \mathcal{X} \times \mathcal{X} \rightarrow [0, \infty)$ and $R(x, y) > 0 \iff y \in \mathcal{B}(x)$.
- Let $\{t_k\}_{k \geq 1}$ be a positive sequence of numbers, which is konwn as the temperature.

[†]The neighborhood structer can be quite different in discrete optimization compared to continuous optimization!

- Simulated annealing algorithm for deterministic optimization:
 - **Initialization:** Arbitrarily choose $\mathbf{X}_0 \in \mathcal{X}$; set iteration index $k = 0$.
 - **At Iteration k :**
 - **Sampling:** Sample a candidate solution $\mathbf{Y}_{k+1} \in \mathcal{B}(\mathbf{X}_k)$ according to distribution $R(\mathbf{X}_k, \cdot)$, i.e.,

$$\mathbb{P}(\mathbf{Y}_{k+1} = \mathbf{y} | \mathbf{X}_k = \mathbf{x}) = R(\mathbf{x}, \mathbf{y}).$$

- **Evaluation:** No need in the deterministic optimization.
- **Updating:** Let

$$\mathbf{X}_{k+1} := \begin{cases} \mathbf{Y}_{k+1}, & \text{with probability } \exp\left\{\frac{-[g(\mathbf{Y}_{k+1}) - g(\mathbf{X}_k)]^+}{t_{k+1}}\right\}, \\ \mathbf{X}_k, & \text{otherwise;} \end{cases}$$

set $k \leftarrow k + 1$.

- To ensure the simulated annealing algorithm for deterministic optimization is globally convergent, i.e.,

$$\text{dist}(\mathbf{X}_k, \mathcal{S}) \xrightarrow{a.s.} 0, \text{ as } k \rightarrow \infty,$$

Hajek (1988, Theorem 1) gives a sufficient condition.

- $R(x, y)$ satisfies weak reversibility; a sufficient example is that

$$R(x, y) := \begin{cases} \frac{1}{|\mathcal{B}(x)|}, & \text{if } y \in \mathcal{B}(x), \\ 0, & \text{otherwise,} \end{cases}$$

with symmetric neighborhood, i.e., $y \in \mathcal{B}(x) \iff x \in \mathcal{B}(y)$.

- $\{t_k\}_{k \geq 1}$ takes the form

$$t_k = \frac{c}{\ln(k+1)},$$

where c is sufficiently large.[†]

[†] $c \geq d^*$, where d^* is the maximum depth (Hajek (1988, p313)) of the local but not global optimal solutions.

- Simulated annealing algorithm for black-box DOvS (Gelfand and Mitter 1989):

- **Initialization:** Arbitrarily choose $\mathbf{X}_0 \in \mathcal{X}$; set iteration index $k = 0$.
- **At Iteration k :**
 - **Sampling:** Sample a candidate solution $\mathbf{Y}_{k+1} \in \mathcal{B}(\mathbf{X}_k)$ according to distribution $R(\mathbf{X}_k, \cdot)$, i.e.,

$$\mathbb{P}(\mathbf{Y}_{k+1} = \mathbf{y} | \mathbf{X}_k = \mathbf{x}) = R(\mathbf{x}, \mathbf{y}).$$

- **Evaluation:** Let $\hat{g}(\mathbf{Y}_{k+1}) := \frac{1}{n_{k+1}} \sum_{i=1}^{n_{k+1}} G(\mathbf{Y}_{k+1}, \xi_i)$,
 $\hat{g}(\mathbf{X}_k) := \frac{1}{n_{k+1}} \sum_{i=1}^{n_{k+1}} G(\mathbf{X}_k, \xi_i)$.[†]
- **Updating:** Let

$$\mathbf{X}_{k+1} := \begin{cases} \mathbf{Y}_{k+1}, & \text{with probability } \exp\left\{\frac{-[\hat{g}(\mathbf{Y}_{k+1}) - \hat{g}(\mathbf{X}_k)]^+}{t_{k+1}}\right\}, \\ \mathbf{X}_k, & \text{otherwise;} \end{cases}$$

set $k \leftarrow k + 1$.

[†] ξ_i in $G(\mathbf{Y}_{k+1}, \xi_i)$ and ξ_i in $G(\mathbf{X}_k, \xi_i)$ denote different randomness; written in this way just for notation simplicity.

- Gelfand and Mitter (1989) show that if

$$\widehat{g}(\mathbf{Y}_{k+1}) | \mathbf{Y}_{k+1} = \mathbf{y} \sim \mathcal{N}(g(\mathbf{y}), \sigma_{k+1}^2),$$

such that $\sigma_k = o(t_k)$, then the simulated annealing algorithm used for DOvS has the same global convergence as its counterpart used for deterministic optimization.

- A sufficient condition is that:
 - $G(\mathbf{x}, \xi) \sim \mathcal{N}(g(\mathbf{x}), \sigma^2(\mathbf{x}))$ with $\sigma^2(\mathbf{x}) \leq \sigma^2 < \infty$ for all $\mathbf{x} \in \mathcal{X}$.
 - $\{n_k\}_{k \geq 1}$ satisfies $\lim_{k \rightarrow \infty} \frac{1}{t_k \sqrt{n_k}} = 0$, i.e., $n_k := t_k^{-\alpha}$ with $\alpha > 2$.
- Alrefaei and Andradóttir (1999) propose a modified simulated annealing algorithm for DOvS, which is also globally convergent:
 - temperature t_k is constant;
 - the current best solution is chosen in a different way.

- Convergent Optimization via Most-Promising-Area Stochastic Search (COMPASS) is a **locally convergent** algorithm for black-box algorithm proposed by [Hong and Nelson \(2006\)](#).
- It can be used when the discrete feasible set is finite (i.e., fully constrained) or infinite (i.e., partially constrained or unconstrained).

- COMPASS for DOvS [Hong and Nelson \(2006\)](#):
 - **Initialization:** Arbitrarily choose $\mathbf{x}_0 \in \mathcal{X}$; set $\mathbf{x}_0^* = \mathbf{x}_0$ and $\mathcal{V}_0 = \{\mathbf{x}_0\}$; take observations according to a simulation allocation rule (SAR) from \mathbf{x}_0 ; let $\mathcal{P}_0 = \mathcal{X}$; set iteration index $k = 0$.
 - **At Iteration k :**
 - **Sampling:** Sample m solutions uniformly and independently from \mathcal{P}_k , denoted as $\{\mathbf{x}_{k1}, \dots, \mathbf{x}_{km}\}$; let $\mathcal{V}_{k+1} := \mathcal{V}_k \cup \{\mathbf{x}_{k1}, \dots, \mathbf{x}_{km}\}$ be the estimation set.
 - **Evaluation:** For each $\mathbf{x} \in \mathcal{V}_{k+1}$, take *additional* observations according to the SAR.
 - **Updating:** Update \mathcal{P}_{k+1} ; choose the solution in \mathcal{V}_{k+1} with smallest estimated function value as \mathbf{x}_{k+1}^* ; set $k \leftarrow k + 1$.

- The way to construct \mathcal{P}_k – the most promising area:

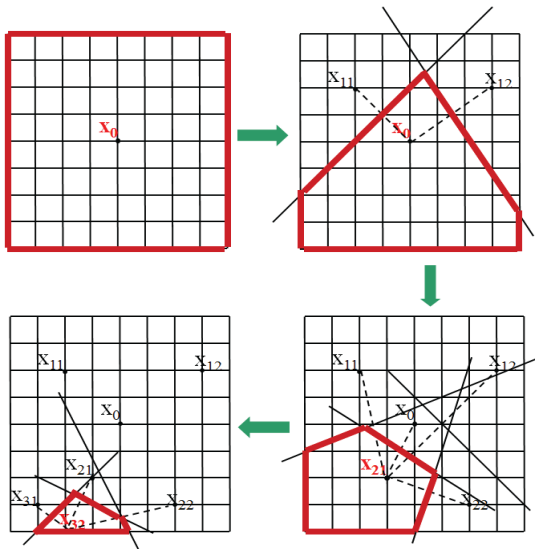


Image from [Jeff Hong](#)



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- In many commercial simulation softwares, like Arena, AnyLogic, Simio and FlexSim, OptQuest is integrated for simulation optimization.
- OptQuest is based on a combination of methods, including linear/integer programming, heuristics and metaheuristics.
 - It is robust when used to solve practical OvS problems;
 - but it has no provable convergence for OvS problems.
- None of those OvS algorithms have been integrated into the commercial simulation softwares yet.
- So, for researchers in the field of OvS, there is still a long way to go...