



# Stochastic Trust-Region Response-Surface Method (STRONG) – A New Response-Surface Framework for Simulation Optimization

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# Problem Definition

Consider the following simulation optimization problem:

$$\min_{x \in \mathbb{X}^p} \mathbb{E}[G(x)],$$

where

- $x$  is the vector of continuous decision variables;
- $G(x)$  is the stochastic response evaluated at  $x$ ;
- $\mathbb{X}^p$  is the  $p$ -dimensional decision space (or "region of operability" in terminology of the RSM)

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## Trust region

- A trust region at a solution  $x'$  with a radius  $\Delta > 0$  is

$$B(x', \Delta) = \{x \in \mathbb{X}^p : \|x - x'\| \leq \Delta\}$$

# Assumptions

1. The objective function  $g(x)$  is bounded below, twice differentiable, and there exist two positive constants,  $\alpha_1$  and  $\beta_1$ , such that  $\|\nabla g(x)\| \leq \alpha_1$  and  $\|H(x)\| \leq \beta_1$ .
2. The estimators of  $g(x)$  and  $\nabla g(x)$  satisfy  $\sup_{x \in \mathbb{X}^p} |\bar{G}(x, n) - g(x)| \rightarrow 0$  w.p.1 as  $n \rightarrow \infty$ , and  $\sup_{x \in \mathbb{X}^p} |\bar{D}(x, m) - \nabla g(x)| \rightarrow 0$  w.p.1 as  $m \rightarrow \infty$ .

# First- and second-order models

First- and second-order model at iteration  $k$ :

$$r_k(x) = \hat{g}_k(x_k) + \hat{\nabla} g_k^T(x_k)(x - x_k),$$

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Cauchy Point Calculation:

1. Find the steepest descent direction

$$d_k = \operatorname{argmin}\{\hat{g}_k(x_k) + \hat{\nabla} g_k^T(x_k)d : \|d\| \leq \Delta_k\};$$

2. Choose a step size

$$\tau_k = \operatorname{argmin}\{r_k(\tau d_k) : \tau > 0, \|\tau d_k\| \leq \Delta_k\}.$$

3. Let  $x_k^* = x_k + \tau_k d_k$ .

## RC (Ratio-Comparison) test

The RC test computes

$$\rho_k = \frac{\hat{g}_k(x_k) - \hat{g}_k(x_k^*)}{r_k(x_k) - r_k(x_k^*)}$$

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Let  $0 < \eta_0 < \eta_1 < 1$ , for example, set  $\eta_0 = 1/4, \eta_1 = 3/4$ .

- If  $\rho_k$  is **large** ( $\rho_k \geq \eta_1$ ), which implies that the new observed solution is significantly better than the current one, the new solution will be accepted.

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- If  $\rho_k$  is **close to 0 or negative** ( $\rho_k < \eta_0$ ), which implies that the “observed reduction” does not agree with the “predicted reduction”, the new solution will be rejected.

## SR (Sufficient-Reduction) test

The SR test is defined as

$$H_0 : g(x_k) - g(x_k^*) \leq \eta_0^2 \zeta_k \quad \text{v.s.} \quad H_1 : g(x_k) - g(x_k^*) > \eta_0^2 \zeta_k,$$

Let  $0 < \eta_0 < \eta_1 < 1$ , for example, set  $\eta_0 = 1/4, \eta_1 = 3/4$ . where

$$\begin{aligned} \zeta_k &:= \|\hat{\nabla} g_k(x_k)\| \Delta_k, \\ \zeta_k &:= \frac{1}{2} \|\hat{\nabla} g_k(x_k)\| \min\left\{ \frac{\|\hat{\nabla} g_k(x_k)\|}{\|\hat{H}_k(x_k)\|}, \Delta_k \right\}. \end{aligned}$$

in first- or second-order models respectively. If  $H_0$  is rejected, we then conclude that the new solution yields a sufficient reduction.

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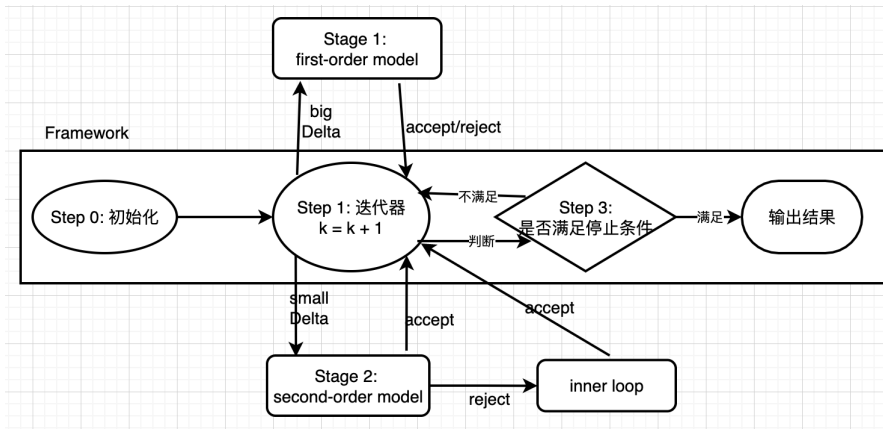
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3. Simulate several observations at  $x_k^*$  and estimate  $g(x_k^*)$ ;
4. Conduct ratio-comparison (RC) and sufficient-reduction (SR) tests to **examine the quality** of  $x_k^*$  and to update  $x_{k+1}$  and the size of trust region  $\Delta_{k+1}$ .

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# STRONG-Framework

- Step 0. Set the iteration count  $k = 0$ . Select an initial solution  $x_0$ , initial sample size of the center point  $n_0$  and of the gradient estimator  $m_0$ , initial trust region size  $\Delta_0$ , the switch threshold  $\tilde{\Delta}$  satisfying  $\Delta_0 > \tilde{\Delta} > 0$ , and constants  $\eta_0, \eta_1, \gamma_1$ , and  $\gamma_2$  satisfying  $0 < \eta_0 < \eta_1 < 1$  and  $0 < \gamma_1 < 1 < \gamma_2$ .

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- Step 1. Let  $k = k + 1$ . If  $\Delta_k > \tilde{\Delta}$ , go to **Stage I**; otherwise, go to **Stage II**.
- Step 2. If the termination criterion is satisfied, stop and **return** the solution. Otherwise, go to **Step 1**.

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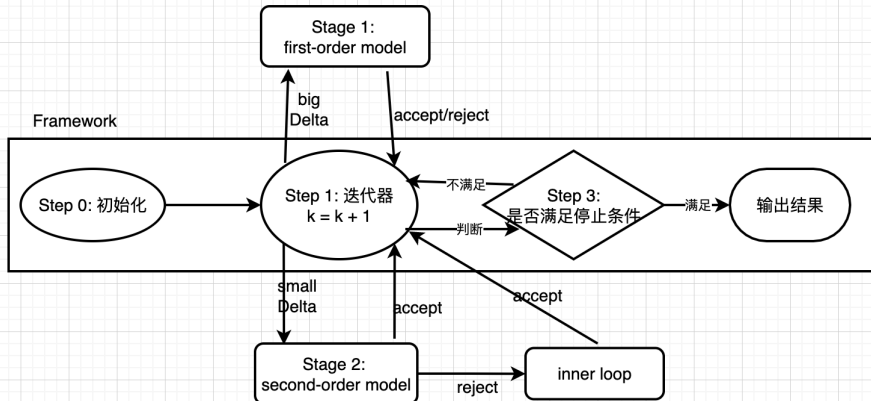
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# Thanks

*Thanks for listening.*

