

MEM6804 Modeling and Simulation for Logistics & Supply Chain



物流与供应链建模与仿真

Theory Analysis

Lecture 9: Output Analysis II: Comparison

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- 2 Comparison of Two Designs
 - ▶ Significant Difference
 - ▶ Independent Sampling
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 - ▶ Ranking and Selection Review
 - ▶ Multi-Arm Bandit Problem



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- We have learnt how to estimate the *absolute performance* of a simulation model.
- We now discuss how to compare two or more simulation models, i.e. to estimate their *relative performance*.
- Here, different simulation models may refer to different designs, operation policies, etc., of a simulated system; in this lecture we simply call them *different (system) designs*.
- It is one of the most important uses of simulation.

- **Key Question:** Are the observed differences due to
 - the **actual differences** on the expected performance of system designs?
 - or the **random errors** in the simulation outputs?
- The comparison can be classified into two types:
 - Two system designs: using confidence interval of the difference.
 - Multiple (more than two) system designs: selection of the best.

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Comparison of Two Designs

- Let θ_1 and θ_2 be the mean performance of the two system designs in simulation.
- To compare θ_1 and θ_2 , we simply construct the point and interval estimates of $\theta_1 - \theta_2$
- Suppose we have the simulation output data from simulation of two system designs.[†]

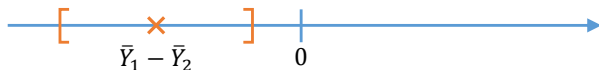
System	Replication				Sample Mean	Sample Variance
	1	2	...	R_i		
1	Y_{11}	Y_{21}	...	$Y_{R_1 1}$	\bar{Y}_1	S_1^2
2	Y_{12}	Y_{22}	...	$Y_{R_2 2}$	\bar{Y}_2	S_2^2

- Point estimator of $\theta_1 - \theta_2$: $\bar{Y}_1 - \bar{Y}_2$.
- Approximate $1 - \alpha$ CI: $\bar{Y}_1 - \bar{Y}_2 \pm t_{v, 1-\alpha/2} \times \text{s.e.}(\bar{Y}_1 - \bar{Y}_2)$.
 - $\text{s.e.}(\bar{Y}_1 - \bar{Y}_2)$ is the estimator of standard error of $\bar{Y}_1 - \bar{Y}_2$; see more details about this quantity and v later.

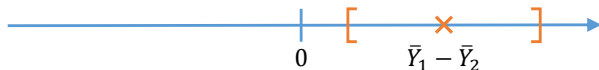
[†]The notation here is different from that in Lec 7; the second subscript indicates different system designs.

Comparison of Two Designs

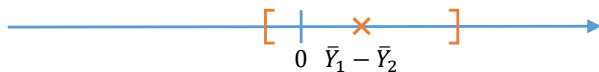
- Case 1 – Strong evidence that $\theta_1 < \theta_2$:



- Case 2 – Strong evidence that $\theta_1 > \theta_2$:



- Case 3 – No strong evidence that one is larger than the other:



- It does not imply $\theta_1 = \theta_2$!

Comparison of Two Designs

- The first two cases are conclusive.
- If in case 3, then we increase the number of replications R_1 and/or R_2 , after which the CI would likely shift, and definitely shrink in length.
- We will shrink the CI until case 1 or 2 is achieved, or the confidence interval is so narrow, which suggests that we do not need to separate them.

- For the comparison of performance of two designs, there is an important distinction between
 - *statistically significant difference* (统计意义上的显著区别);
 - *practically significant difference* (实际意义上的显著区别).
- **Statistical** significance answers the following questions:
 - Is the observed difference $\bar{Y}_1 - \bar{Y}_2$ larger than its variability?
 - Have we collected enough data to be confident that the observed difference is real (not just by chance)?
- **Practical** significance answers the following question:
 - Is the true difference $|\theta_1 - \theta_2|$ large enough so it is worthwhile to separate them?

- Cases 1 and 2 imply a statistically significant difference, while case 3 does not.
- In case 1, we may reach the conclusion that $\theta_1 < \theta_2$ and decide that design 2 is better (suppose larger is better).
- However, if the actual difference $|\theta_1 - \theta_2|$ is very small, then it might not be worth the cost to replace design 1 with design 2.
- Confidence intervals do not answer the question of practical significance directly.
 - Instead, they bound, with probability $1 - \alpha$, the true difference $\theta_1 - \theta_2$ within the range $\bar{Y}_1 - \bar{Y}_2 \pm t_{v, 1-\alpha/2} \times \text{s.e.}(\bar{Y}_1 - \bar{Y}_2)$.
 - Whether a difference within these bounds is practically significant depends on the particular problem.

- Independent sampling means that **different** random number streams are used to simulate the two systems.
 - All the observations of system 1 $\{Y_{r1} : r = 1, \dots, R_1\}$ are statistically independent of all the observations of system 2 $\{Y_{r2} : r = 1, \dots, R_2\}$.

- Suppose $\text{Var}(Y_{r1}) = \sigma_1^2$ and $\text{Var}(Y_{r2}) = \sigma_2^2$. Due to the independence,

$$\text{Var}(\bar{Y}_1 - \bar{Y}_2) = \text{Var}(\bar{Y}_1) + \text{Var}(\bar{Y}_2) = \frac{\sigma_1^2}{R_1} + \frac{\sigma_2^2}{R_2}.$$

- Standard error of $\bar{Y}_1 - \bar{Y}_2$ is $\sqrt{\frac{\sigma_1^2}{R_1} + \frac{\sigma_2^2}{R_2}}$.
- σ_i^2 is estimated via sample variance

$$S_i^2 = \frac{1}{R_i - 1} \sum_{r=1}^{R_i} (Y_{ri} - \bar{Y}_i)^2.$$

- Standard error of $\bar{Y}_1 - \bar{Y}_2$ is estimated via

$$\text{s.e.}(\bar{Y}_1 - \bar{Y}_2) = \sqrt{\frac{S_1^2}{R_1} + \frac{S_2^2}{R_2}}.$$

- The $1 - \alpha$ CI is approximated by

$$\bar{Y}_1 - \bar{Y}_2 \pm t_{v, 1-\alpha/2} \times \text{s.e.}(\bar{Y}_1 - \bar{Y}_2). \quad (2)$$

where $\text{s.e.}(\bar{Y}_1 - \bar{Y}_2)$ is given in (1), and the degree of freedom v is

$$v = \frac{[S_1^2/R_1 + S_2^2/R_2]^2}{[S_1^2/R_1]^2/(R_1 - 1) + [S_2^2/R_2]^2/(R_2 - 1)}.$$

- The approximated CI (2) is called the *Welch confidence interval* (Welch 1938).
 - Sometimes, people will round v to integer for convenience.

- If $R_1 = R_2 = R$, or we are willing to discard some observations from the system design on which we actually have more data, we can pair Y_{r1} with Y_{r2} to define $Z_r = Y_{r1} - Y_{r2}$, for $r = 1, \dots, R$.

- Point estimator of $\theta_1 - \theta_2$: $\bar{Z} = \frac{1}{R} \sum_{r=1}^R Z_r = \bar{Y}_1 - \bar{Y}_2$.

$$\begin{aligned} \text{Var}(\bar{Z}) &= \frac{\text{Var}(Z_r)}{R} = \frac{\text{Var}(Y_{r1} - Y_{r2})}{R} = \frac{\sigma_1^2 + \sigma_2^2}{R} \\ &= \text{Var}(\bar{Y}_1 - \bar{Y}_2) = \text{Var}(\bar{Y}_1) + \text{Var}(\bar{Y}_2) = \frac{\sigma_1^2 + \sigma_2^2}{R}. \end{aligned} \quad (3)$$

- To estimate $\text{Var}(Z_r)$, instead of estimating σ_1^2 and σ_2^2 separately, we can directly use

$$S^2 = \frac{1}{R-1} \sum_{r=1}^R (Z_r - \bar{Z})^2. \quad (4)$$

- Approximate $1 - \alpha$ CI:

$$\bar{Z} \pm t_{R-1, 1-\alpha/2} \frac{S}{\sqrt{R}}. \quad (5)$$



- Common Random Numbers (CRN, also known as correlated sampling): For each replication, the same random numbers are used to simulate both systems.
 - For each replication r , the two estimates, Y_{r1} and Y_{r2} , are correlated.
 - In this case, R_1 and R_2 must be equal, say, $R_1 = R_2 = R$.
- The purpose of using CRN is to induce a **positive** correlation between Y_{r1} and Y_{r2} for each r and thus to achieve a variance reduction in the point estimator of $\theta_1 - \theta_2$, \bar{Z} .

$$\text{Var}(\bar{Z}) = \frac{\text{Var}(Y_{r1} - Y_{r2})}{R} = \frac{\sigma_1^2 + \sigma_2^2 - 2\rho_{12}\sigma_1\sigma_2}{R}. \quad (6)$$

- $\text{Var}(\bar{Z})$ in (6) is smaller than that in (3) \implies higher precision of point estimator.
- CI is still computed via (4) and (5), but the width will be smaller \implies higher precision.

- It is never enough to simply use the same seed for the random-number generator(s):
 - The random numbers must be synchronized: each random number used in one model for some purpose should be used for the same purpose in the other model.
 - E.g., if the i th random number is used to generate a service time at work station 2 for the 5th arrival in model 1, the i th random number should be used for the very same purpose in model 2.
- The CRN idea is also used when we validate simulation model via input-output transformation, where we prefer to compare the model and actual system under the same historical input, rather than generate the input from input model.

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Comparison of Multiple Designs

- Suppose there are $k > 2$ system designs in total.
- The interested mean performance of design i is θ_i (unknown).
- Some possible goals:
 - ① Estimation of each parameter θ_i .
 - ② Comparison of each θ_i to a control, say, θ_1 (θ_1 can represent the mean performance of an existing system).
 - ③ All pairwise comparisons.
 - ④ Selection of the best θ_i (largest or smallest).
- The first three can be achieved by **simultaneous** construction of confidence intervals, whereas the last by some **selection approaches**.
- From now on, without loss of generality, let's *assume the best θ_i is the largest one*.

- Assumption 1: For each design i with mean performance θ_i , the noisy output $Y_{ri} \sim \mathcal{N}(\theta_i, \sigma_i^2)$, for $r = 1, 2, \dots$
- Assumption 2: No CRN is used, i.e., Y_{ri} is independent of Y_{rj} for $i \neq j$.
- Assumption 3 (**indifference-zone**): The gap between the largest θ_i and the second largest θ_i is at least δ , a value known to us.
- Assumption 4 (known variance): σ_i^2 is known, for $i = 1, \dots, k$.
- Bechhofer (1954) first developed a selection procedure, which can ensure the probability of correct selection (PCS):

$$\mathbb{P}\{\text{select the largest } \theta_i\} \geq 1 - \alpha, \quad (7)$$

under Assumptions 1-4, where α is a user specified value and $1 - \alpha > 1/k$.

- Bechhofer's Procedure

- ① Calculate a constant h , which satisfies

$$\mathbb{P}\{Z_i \leq h, i = 1, 2, \dots, k-1\} = 1 - \alpha, \quad (8)$$

where $(Z_1, Z_2, \dots, Z_{k-1})^\top$ has a multivariate normal distribution with means 0, variances 1, and common pairwise correlations $1/2$.

- ② For $i = 1, \dots, k$, let

$$n_i = \left\lceil \frac{2h^2 \sigma_i^2}{\delta^2} \right\rceil. \quad (9)$$

- ③ For $i = 1, \dots, k$, run n_i replications for design i and calculate

$$\bar{Y}_i = \frac{1}{n_i} \sum_{r=1}^{n_i} Y_{ri}.$$

- ④ Select the design with the largest sample mean \bar{Y}_i as the best.

Proof.

Without loss of generality, assume $\theta_k \geq \theta_{k-1} \geq \dots \geq \theta_1$. Then Assumption 3 says, $\theta_k - \theta_{k-1} \geq \delta$, which implies that

$$\theta_k - \theta_i \geq \delta, \quad i = 1, \dots, k-1. \quad (10)$$

$$\begin{aligned} \mathbb{P}\{\text{select } k\} &= \mathbb{P}\{\bar{Y}_i - \bar{Y}_k < 0, \quad i = 1, \dots, k-1\} \\ &= \mathbb{P}\left\{ \frac{\bar{Y}_i - \bar{Y}_k - (\theta_i - \theta_k)}{\sqrt{\sigma_k^2/n_k + \sigma_i^2/n_i}} < \frac{-(\theta_i - \theta_k)}{\sqrt{\sigma_k^2/n_k + \sigma_i^2/n_i}}, \quad i = 1, \dots, k-1 \right\} \\ &= \mathbb{P}\left\{ Z_i < \frac{\theta_k - \theta_i}{\sqrt{\sigma_k^2/n_k + \sigma_i^2/n_i}}, \quad i = 1, \dots, k-1 \right\} \\ &\geq \mathbb{P}\left\{ Z_i < \frac{\theta_k - \theta_i}{\sqrt{\sigma_k^2/(\frac{2h^2\sigma_k^2}{\delta^2}) + \sigma_i^2/(\frac{2h^2\sigma_i^2}{\delta^2})}}, \quad i = 1, \dots, k-1 \right\} \quad (\text{due to (9)}) \\ &= \mathbb{P}\left\{ Z_i < \frac{\theta_k - \theta_i}{\delta/h}, \quad i = 1, \dots, k-1 \right\} \\ &\geq \mathbb{P}\{Z_i < h, \quad i = 1, \dots, k-1\}. \quad (\text{due to (10)}) \end{aligned}$$

Proof. (Cont'd)

Now we only need to check that $\mathbf{Z} = (Z_1, Z_2, \dots, Z_{k-1})^\top$ indeed has a multivariate normal distribution with means 0, variances 1, and common pairwise correlations $1/2$ (except for some rounding error).

Recall that

$$Z_i = \frac{\bar{Y}_i - \bar{Y}_k - (\theta_i - \theta_k)}{\sqrt{\sigma_k^2/n_k + \sigma_i^2/n_i}}, \quad i = 1, \dots, k-1,$$

and $\mathbf{Y} = (\bar{Y}_1, \bar{Y}_2, \dots, \bar{Y}_k)^\top$ is a k -variate normal random vector. So, \mathbf{Z} , as a linear combination of \mathbf{Y} , must be a $(k-1)$ -variate normal random vector.

Besides, $\text{Var}(Z_i) = \frac{\text{Var}(\bar{Y}_i - \bar{Y}_k)}{\sigma_k^2/n_k + \sigma_i^2/n_i} = \frac{\sigma_k^2/n_k + \sigma_i^2/n_i}{\sigma_k^2/n_k + \sigma_i^2/n_i} = 1.$

Moreover, since $n_i = \left\lceil \frac{2h^2\sigma_i^2}{\delta^2} \right\rceil$ in (9), $\frac{\sigma_i^2}{n_i} = \frac{\delta^2}{2h^2}$ approximately, $i = 1, \dots, k.$

For $i \neq j$, $\text{Cov}(Z_i, Z_j) = \text{Cov}\left(\frac{\bar{Y}_i - \bar{Y}_k}{\delta/h}, \frac{\bar{Y}_j - \bar{Y}_k}{\delta/h}\right) = \frac{\text{Cov}(\bar{Y}_k, \bar{Y}_k)}{\delta^2/h^2} = \frac{\sigma_k^2/n_k}{\delta^2/h^2} = \frac{1}{2}.$

Hence, by (8) and (11), $\mathbb{P}\{\text{select } k\} \geq 1 - \alpha.$



- Assumption 3 (indifference-zone) can be **relaxed** by *softening* the selection target to probability of good selection (PGS):

$$\mathbb{P} \left\{ \left| \text{selected } \theta_i - \max_{1 \leq i \leq k} \theta_i \right| < \delta \right\} \geq 1 - \alpha.$$

- Rinott (1978) proposed a procedure which can still guarantee the PCS in (7) while relaxing Assumption 4 (*known* variance), i.e., allowing *unknown* variances.
 - It requires an initial stage to estimate σ_i^2 by sample variance.
 - The proof is more complicated.
- Procedures like Bechhofer's or Rinott's are simple to implement, but the efficiency may be low.
 - The designed sample size (or, replication number), n_i , may be larger than necessary (too conservative).

- More sample efficient procedures should be in a sequential manner.
 - Take observations sequentially, i.e., one at a time.
 - Eliminate designs from continued sampling when it is statistically clear that they are inferior.
 - Simulation for a problem with a single dominant alternative may terminate very quickly.
- Paulson (1964) proposed fully sequential procedures, which can guarantee the PCS in (7), under Assumptions 1-3 and (a) *common known* variance or (b) *common unknown* variance.

- Suppose $\sigma_1^2 = \sigma_2^2 = \dots = \sigma_k^2 = \sigma^2$ and σ^2 is known (*common known variance*).
- Let $\bar{Y}_i(r)$ be the sample mean of the first r observations.
- Paulson's Procedure

- ① Let $0 < \lambda < \delta$ (a good choice is $\lambda = \delta/2$), and

$$a = \ln\left(\frac{k-1}{\alpha}\right) \frac{\sigma^2}{\delta - \lambda}.$$

Let $I = \{1, 2, \dots, k\}$ and $r = 0$.

- ② Let $r \leftarrow r + 1$. Take one observation from each alternative in I and compute $\bar{Y}_i(r)$, $\forall i \in I$.
- ③ Let $I^{\text{old}} = I$ and

$$I = \left\{ \ell \in I^{\text{old}} : \bar{Y}_\ell(r) \geq \max_{i \in I^{\text{old}}} \bar{Y}_i(r) - \max\{0, a/r - \lambda\} \right\}.$$

If $|I| > 1$, then go to Step 2; otherwise, select the alternative left in I as the best.

- [Kim and Nelson \(2001\)](#) proposed a fully sequential procedure \mathcal{KN} , which extends Paulson's procedure, by allowing *unequal* variances and CRN.
- Commercial simulation software, Simio, implements the \mathcal{KN} procedure of [Kim and Nelson \(2001\)](#) as an Add-In, to help user to select the best scenario.

- Ranking and Selection (R&S) problem was first introduced in the 1950s by the statistics community:
 - rank all alternatives
 - select a subset of alternatives
 - select the best alternative (attract the most attention)
- Existing procedures for R&S (selection of the best) problems:
 - frequentist
 - Bayesian

- Frequentist procedures typically aim to deliver the PCS or PGS; see [Kim and Nelson \(2006\)](#) for a review:
 - two-stage procedures: [Bechhofer \(1954\)](#), [Rinott \(1978\)](#)
 - sequential procedures: [Paulson \(1964\)](#), [Kim and Nelson \(2001\)](#), [Hong \(2006\)](#)
- Bayesian procedures often allocate samples to each alternative either to maximize the Bayesian posterior PCS or to minimize the expected opportunity cost; see [Chen et al. \(2015\)](#) for a review:
 - optimal computing budget allocation: [Chen et al. \(2000\)](#), [He et al. \(2007\)](#)
 - value of information: [Chick and Inoue \(2001\)](#), [Chick et al. \(2010\)](#)
 - knowledge gradient: [Frazier et al. \(2008\)](#), [Frazier et al. \(2009\)](#)
 - economics of selection procedures: [Chick and Gans \(2009\)](#), [Chick and Frazier \(2012\)](#)

- Emerging research problems that expand classical R&S from different perspectives; see [Hong et al. \(2021\)](#) for a review:
 - large-scale R&S using parallel computing
 - constrained R&S
 - multi-objective R&S
 - R&S with input uncertainty
 - R&S with covariates
- What if the number of candidate designs (feasible solutions) is huge, or countably infinite, or even uncountably infinite?
 - **Simulation Optimization (or called Optimization via Simulation)**

- R&S Problem vs Multi-Arm Bandit (MAB) Problem:

