

正态——正态结构串联系统可靠度的 Bayes 估计*

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摘要 本文利用 Bayes 方法讨论了正态——正态结构串联系统可靠度 $\theta = P_r(X > Y)$ 的估计问题, 把 θ 的后验均值作为它的点估计, 在特殊情况下, 还得到了 θ 的 Bayes 置信限.

关键词 可靠度, Bayes 置信限.

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一个部件或系统称为失效, 如果当其所承受的应力超过它本身的强度时. 而部件或系统的强度 X 及应力 Y 往往是未知的随机变量, 因此估计部件或系统的可靠度 $\theta = P_r(X > Y)$ 是很重要的. 自从 Birnbaum^[1](1956)发表了利用 U 统计量求得的 θ 的 MVUE 以来, 人们在可靠度 θ 的点估计方面作了大量工作. 本文利用 Bayes 方法得到了 θ 的点估计和 θ 的 Bayes 置信限.

一 部件强度相互独立的串联系统承受同一应力时可靠度的估计

设系统是串联的, X_1, X_2, \dots, X_p 为部件的强度, Y 为系统所受的应力, X_1, X_2, \dots, X_p, Y 相互独立且 $X_i \sim N(\mu_i, \sigma^2), i = 1, 2, \dots, p, Y \sim N(\mu, \sigma^2)$, 此时系统的可靠度

$$\begin{aligned} \theta &= P_r(X_1 > Y, \dots, X_p > Y) = P_r(X_1 - Y > 0, \dots, X_p - Y > 0) \\ &= (2\pi)^{-\frac{p}{2}} \sigma^{-p} |A|^{-\frac{1}{2}} \int_{z < 0} \dots \int \exp\left\{-\frac{1}{2}(\underline{z} - \underline{v})^T \frac{A^{-1}}{\sigma^2} (\underline{z} - \underline{v})\right\} d\underline{z}, \end{aligned}$$

其中 $\underline{v} = (v_1, v_2, \dots, v_p)^T, v_i = \mu_i - \mu, i = 1, 2, \dots, p$

$$\underline{Z} = (z_1, z_2, \dots, z_p)^T, A = A_{p \times p} = \begin{pmatrix} 2 & 1 & \dots & 1 \\ 1 & 2 & \dots & 1 \\ \dots & \dots & \dots & \dots \\ 1 & 1 & \dots & 2 \end{pmatrix}$$

设 $X_{ij} = 1, 2, \dots, n_i$ 为 X_i 的观测值, $i = 1, 2, \dots, p, Y_1, Y_2, \dots, Y_{n_{p+1}}$ 为 Y 的观测值. 记

$$N = \sum_{i=1}^{p+1} n_i, \bar{X}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} X_{ij}, i = 1, \dots, p, \bar{Y} = \frac{1}{n_{p+1}} \sum_{j=1}^{n_{p+1}} Y_j,$$

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$$S^2 = (N - P - 1)^{-1} \left[\sum_{i=1}^p \sum_{j=1}^{n_i} (X_{ij} - \bar{X}_i)^2 + \sum_{j=1}^{n_{p+1}} (Y_j - \bar{Y})^2 \right],$$

则 $(\mu_1, \mu_2, \dots, \mu_p, \mu, \sigma)$ 的似然函数是

$$L(\mu_1, \mu_2, \dots, \mu_p, \mu, \sigma) = \sigma^{-N} \exp \left\{ -\frac{1}{2} \sigma^{-2} \left[(N - P - 1) S^2 + \sum_{i=1}^p n_i (\bar{X}_i - \mu_i)^2 + n_{p+1} (\bar{Y} - \mu)^2 \right] \right\}.$$

假定 $(\mu_1, \mu_2, \dots, \mu_p, \mu, \sigma)$ 先验分布为“共轭型”，且在 σ 给定条件下， $\mu_1, \mu_2, \dots, \mu_p, \mu$ 相互独立，即

$$P(\mu_1, \mu_2, \dots, \mu_p, \mu, \sigma) \propto \sigma^{-(p+r+2)} \exp \left\{ -\frac{1}{2} \sigma^{-2} [\tau \beta + (\underline{w} - \underline{m})^T \Lambda (\underline{w} - \underline{m})] \right\},$$

其中 $\underline{w} = (\mu_1, \dots, \mu_p, \mu)^T, \underline{m} = (m_1, m_2, \dots, m_{p+1})^T, \tau > 0, \beta > 0$

$$\Lambda = \Lambda_{(p+1) \times (p+1)} = \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_{p+1} \end{pmatrix}, \lambda_i > 0, i = 1, \dots, p+1.$$

由 Bayes 定理， $(\mu_1, \dots, \mu_p, \mu, \sigma)$ 的后验密度函数为

$$P(\mu_1, \dots, \mu_p, \mu, \sigma | \bar{X}_1, \bar{X}_2, \dots, \bar{X}_p, \bar{Y}, S^2) \propto \sigma^{-(N+p+r+2)} \cdot \exp \left\{ -\frac{1}{2\sigma^2} \left[(N - p - 1) S^2 + \tau \beta + (\bar{X} - \underline{m})^T \Delta (\Delta + \Lambda)^{-1} \Delta (\bar{X} - \underline{m}) \right] - \frac{1}{2\sigma^2} \left[\underline{w} - (\Delta + \Lambda)^{-1} (\Delta \bar{X} + \Lambda \underline{m}) \right]^T (\Delta + \Lambda) \left[\underline{w} - (\Delta + \Lambda)^{-1} (\Delta \bar{X} + \Lambda \underline{m}) \right] \right\}$$

这里 $\bar{X} = (\bar{X}_1, \bar{X}_2, \dots, \bar{Y}, \bar{Y})^T, \Delta = \begin{pmatrix} n_1 & & 0 \\ & \ddots & \\ 0 & & n_{p+1} \end{pmatrix}$

从而在 σ 给定条件下

$$\mu_i \sim N \left(\frac{n_i \bar{X}_i + \lambda_i m_i}{n_i + \lambda_i}, \frac{\sigma^2}{n_i + \lambda_i} \right), i = 1, 2, \dots, p,$$

$$\mu \sim N \left(\frac{\lambda_{p+1} m_{p+1} + n_{p+1} \bar{Y}}{n_{p+1} + \lambda_{p+1}}, \frac{\sigma^2}{n_{p+1} + \lambda_{p+1}} \right).$$

于是

$$E v_i = E[\mu - \mu_i] = (\lambda_{p+1} m_{p+1} + n_{p+1} \bar{Y}) (n_{p+1} + \lambda_{p+1})^{-1} - (\lambda_i m_i + n_i \bar{X}_i) (\lambda_i + n_i)^{-1} \triangleq a_i,$$

$$E[\underline{v}] = \frac{\lambda_{p+1} m_{p+1} + n_{p+1} \bar{Y}}{\lambda_{p+1} + n_{p+1}} \underline{1} - (\Delta_1 + \Lambda_1)^{-1} (\Lambda_1 \underline{m}_1 + \Delta_1 \bar{X}^{(1)}) \triangleq \underline{a}, \quad i = 1, 2, \dots, p$$

其中

$$\underline{1} = (1, 1, \dots, 1)_{1 \times p}^T, \underline{m}_1 = (m_1, m_2, \dots, m_p)^T,$$

$$\bar{X}^{(1)} = (\bar{X}_1, \bar{X}_2, \dots, \bar{X}_p)^T, \underline{\mu} = (\mu_1, \dots, \mu_p)^T,$$

$$\underline{v} = (v_1, \dots, v_p)^T, \underline{a} = (a_1, \dots, a_p)^T,$$

$$\Lambda_1 = \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_p \end{pmatrix}, \Delta_1 = \begin{pmatrix} n_1 & & 0 \\ & \ddots & \\ 0 & & n_p \end{pmatrix}.$$

所以

$$\frac{1}{\sigma^2} \text{cov}(\underline{v}, \underline{v}) = (\Delta_1 + \Lambda_1)^{-1} + (\lambda_{p+1} + n_{p+1})^{-1} \underline{1} \underline{1}^T \triangleq B,$$

$$P(\underline{v}/\sigma, \bar{X}_1, \dots, \bar{X}_p, \bar{Y}, S^2) = (2\pi)^{-\frac{p}{2}} \sigma^{-p} |B|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2\sigma^2}(\underline{v} - \underline{a})^T B^{-1}(\underline{v} - \underline{a})\right\}.$$

又由 σ^2 的后验分布密度

$$P(\sigma/\bar{X}_1, \dots, \bar{X}_p, \bar{Y}, S^2) = \frac{2\left(\frac{b}{2}\right)^{\frac{N+r}{2}} \cdot \exp\left\{-\frac{\sigma^2}{2}b\right\}}{\sigma^{(N+r+1)} \Gamma\left(\frac{N+r}{2}\right)} I_{(\sigma>0)},$$

$$(b = (N-p-1)S^2 + r\beta + (\underline{m} - \bar{X})^T \Delta (\Delta + \Lambda)^{-1} \Lambda (\underline{m} - \bar{X})).$$

$(v_1, \dots, v_p, \sigma)$ 的后验分布密度函数为

$$P\{\underline{v}, \sigma/\bar{X}_1, \dots, \bar{X}_p, \bar{Y}, S^2\} = \frac{2\left(\frac{b}{2}\right)^{\frac{N+r}{2}} \exp\left\{-\frac{1}{2\sigma^2}[b + (\underline{v} - \underline{a})^T B^{-1}(\underline{v} - \underline{a})]\right\}}{(2\pi)^{\frac{p}{2}} |B|^{\frac{1}{2}} \Gamma\left(\frac{N+r}{2}\right) \sigma^{N+r+1}} I_{(\sigma>0)}.$$

因此得 θ 的 Bayes 估计量

$$\begin{aligned} E[\theta/\bar{X}_1, \dots, \bar{X}_p, \bar{Y}, S^2] &= \frac{b^{\frac{1}{2}(N+r)} |A|^{-\frac{1}{2}} |B|^{-\frac{1}{2}}}{2^{\frac{1}{2}(N+r+2p-2)} \pi^p \Gamma\left(\frac{N+r}{2}\right)} \int_{z < 0} \dots \int_{\sigma > 0} \dots \int_{\underline{v}} \sigma^{-(N+2p+r+1)} \\ &\quad \cdot \exp\left\{-\frac{1}{2\sigma^2}[(\underline{v} - \underline{z})^T A^{-1}(\underline{v} - \underline{z}) + b + (\underline{v} - \underline{a})^T B^{-1}(\underline{v} - \underline{a})]\right\} d\underline{v} d\sigma d\underline{z} \\ &= \frac{\Gamma\left(\frac{N+p+r}{2}\right) b^{-\frac{p}{2}}}{\pi^{\frac{p}{2}} |A+B| \Gamma\left(\frac{N+r}{2}\right)} \int_{z < \underline{a}} \dots \int \left[1 + \frac{z^T (A+B)^{-1} z}{b}\right]^{-\frac{1}{2}(N+r)} dz \end{aligned}$$

注意到 $\lim_{N \rightarrow \infty} \frac{b}{N} = \sigma^2$, $\lim_{\substack{N \rightarrow \infty \\ 1 \leq i \leq p+1}} (A+B) = A$ (a. s.) 知 $E[\theta/\bar{X}_1, \dots, \bar{X}_p, \bar{Y}, S^2]$ 为 θ 的强相合估计。

二 部件强度独立同分布的串联系统承受 同一应力时可靠度的估计

设系统的 p 个串联部件的强度 $X_1, \dots, X_p, i. i. d \sim N(\mu, \sigma^2)$, 而系统的应力 $Y \sim N(v, \sigma^2)$, 设 X_1, \dots, X_p 与 Y 相互独立, 则系统可靠度

$$\theta = P_r(X_1 > Y, \dots, X_p > Y) = (2\pi)^{-\frac{p}{2}} |A|^{-\frac{1}{2}} \int_{z < \frac{\underline{a}}{\sigma}} \dots \int \exp\left\{-\frac{1}{2} z^T A^{-1} z\right\} dz,$$

其中 $1 = (1, \dots, 1)_{1 \times p}^T$, $\tilde{z} = (z_1, \dots, z_p)^T$, $m = v - \mu$, $A = \begin{pmatrix} 2 & 1 & \dots & 1 \\ 1 & 2 & \dots & 1 \\ \dots & \dots & \dots & \dots \\ 1 & 1 & \dots & 2 \end{pmatrix}_{p \times p}$

若 X_1, \dots, X_N 为 $N(\mu, \sigma^2)$ 的样本, Y_1, \dots, Y_M 为 $N(v, \sigma^2)$ 的样本, $\bar{X} = \frac{1}{N} \sum_{j=1}^N X_j$, $\bar{Y} = \frac{1}{M} \sum_{j=1}^M Y_j$, $S^2 = (M + N - 2)^{-1} [\sum_{i=1}^N (X_i - \bar{X})^2 + \sum_{i=1}^M (Y_i - \bar{Y})^2]$, (μ, v, σ) 的联合先验密度为“无信息先验” $p(\mu, v, \sigma) \propto \frac{1}{\sigma} I_{(\sigma < 0)}$, 则 θ 的后验均值

$$E[\theta | \bar{X}, \bar{Y}, S^2] = \frac{(MN)^{\frac{1}{2}} [(M + N - 2)S^2]^{-\frac{1}{2}} \Gamma(\frac{N + M + P - 2}{2})}{\pi^{p/2} [P(M + N + MN) + MN]^{p/2} \Gamma(\frac{M + N - 2}{2})} \cdot \int_{\tilde{z} < \bar{Y} - \bar{X}} \left\{ 1 + [(M + N - 2)S^2]^{-1} \tilde{z}^T [I - \frac{(MN + M + N)11^T}{P(M + N + MN) + MN}] \tilde{z} \right\}^{-\frac{1}{2}(M + N + P - 2)} d\tilde{z}.$$

由 θ 为 $\frac{m}{\sigma}$ 的单调函数, 令 $t = \frac{m}{\sigma}$, 则 t 的后验密度函数是

$$P(t | \bar{X}, \bar{Y}, S^2) = \frac{(MN)^{\frac{1}{2}} [(M + N - 2)S^2]^{\frac{1}{2}(M + N - 2)} \exp\{-\frac{1}{2} \frac{MN}{M + N} t^2\}}{(2\pi)^{\frac{1}{2}} (M + N)^{\frac{1}{2}} [(M + N - 2)S^2 + \frac{MN}{M + N} a^2]^{\frac{1}{2}(M + N - 2)} \Gamma(\frac{M + N - 2}{2})} \cdot \sum_{j=0}^{\infty} \frac{\Gamma(\frac{M + N + j - 2}{2})}{\Gamma(j + 1)} \left(\frac{\sqrt{2} \frac{MN}{M + N} a t}{[(M + N - 2)S^2 + \frac{MN}{M + N} a^2]^{\frac{1}{2}}} \right)^j,$$

其中 $a = \bar{Y} - \bar{X}$. 所以

$$E(t) = \frac{\sqrt{2} a}{[(M + N - 2)S^2]^{\frac{1}{2}}} \cdot \frac{\Gamma(\frac{M + N - 1}{2})}{\Gamma(\frac{M + N - 2}{2})},$$

$$D(t) = \frac{(M + N - 2)\Gamma^2[\frac{1}{2}(M + N - 2)] - 2\Gamma^2[\frac{1}{2}(M + N - 1)]}{[(M + N - 2)S^2]^2 \Gamma^2[\frac{1}{2}(M + N - 2)]} a^2 + \frac{M + N}{MN}.$$

令 $\rho = \frac{t - E(t)}{\sqrt{D(t)}}$, 由[3]得 ρ 的特征函数

$$E[\exp(i\rho(\beta))] = \exp\left\{-\frac{\beta^2}{2} \frac{M + N}{MN} \cdot \frac{1}{D(t)} - i\beta E(t) \cdot \frac{1}{D(t)}\right\} \cdot \sum_{j=1}^{\infty} \frac{(\sqrt{2} i\beta)^j}{\Gamma(j + 1)} \left[\frac{a [(M + N - 2)S^2]^{-\frac{1}{2}}}{\sqrt{D(t)}} \right]^j \frac{\Gamma[\frac{1}{2}(M + N + j - 2)]}{\Gamma[\frac{1}{2}(M + N - 2)]}$$

利用 Stirling 公式可得 $E[\exp(i\rho\beta)] \simeq \exp\{-\frac{\beta}{2}\}$. 即 ρ 的分布近似于 $N(0,1)$, 从而

$$P_r\{\theta_1 < \theta < \theta_2\} = P_r\{t_1 < t < t_2\} \approx \Phi(\rho_2) - \Phi(\rho_1),$$

其中 $\theta_i = (2\pi)^{-\frac{1}{2}} |A|^{-\frac{1}{2}} \int \dots \int_{z < t_i} \exp\{-\frac{1}{2} z^T A^{-1} z\} dz$, $\rho_i = \frac{t_i - E(t)}{\sqrt{D(t)}}$, $i = 1, 2$.

如令 $0 < \alpha < 1$, $\Phi(\rho_\alpha) = \alpha$, $t_\alpha = E(t) + \rho_\alpha \sqrt{D(t)}$, 则 θ 的置信水平 $1-\alpha$ 的近似置信下界为

$$\theta_\alpha (2\pi)^{-\frac{1}{2}} |A|^{-\frac{1}{2}} \int \dots \int_{z < t_\alpha} \exp\{-\frac{1}{2} z^T A^{-1} z\} dz,$$

即 $P_r\{\theta_\alpha < \theta\} = P_r\{t_\alpha < t\} = 1 - \alpha$.

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Bayes Estimation on the Reliability of Normal-Normal Structural Series System

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Abstract

We discuss the estimation problem on the reliability $\theta = P_r(x > Y)$ of Normal-Normal structural series system. The posterror mean of θ is considered here as its point estimator. In some cases, the Bayes confidence bound of θ is given.

Keywords reliability, Bayes confidence bound.