Mixing Apples and Oranges: Complex System Reliability Estimation with Mixed Modal Testing

An Application to Defense Missile Systems

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Outline

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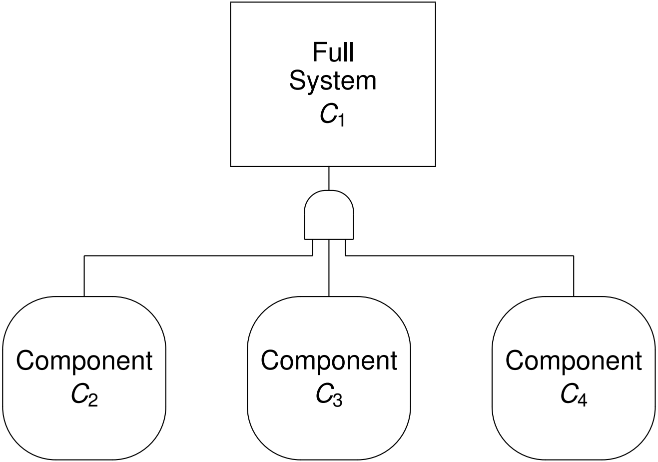
- Question to be considered: Should all sources impact assessment?

A Simple System



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  4. prior distribution: before any data collection, the view of the reliabilities (e.g., expert opinion, historical data, data on similar systems)

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  1. Reparameterized Beta distributions
  2. Uniform prior distributions at various levels
  3. Commensurate/Power prior distributions based on historical data

Outline

Model for System Likelihood

- Likelihood for SYSTEM LEVEL DATA (y_S): Lifetime, Vibration, etc.

$$f_S(y_S|\Theta) = \prod_{k=1}^{n_s} \sum_{i=2}^{4} f_i(y_{S_k}|\Theta_i) \prod_{j \neq i} (R(y_{S_k}|\Theta)).$$

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- n_S is the number of system tests
- Derived from distribution of minimum.
- Above representation is for series systems (similar representations available for parallel systems)

Model for Component Likelihood

- Likelihood for SYSTEM LEVEL DATA (x_S, n_S): Pass/Fail (Series)

$$g_S(x_S|R_i(t*)) \propto (\prod_{i=1}^{n_C} R_i(t*))^{x_S}(1 - \prod_{i=1}^{n_C} R_i(t*))^{n_S - x_S}$$

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- Incorrectly specified system structures have huge impact.

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- Model checking advised!

Model for Component Likelihood

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- Likelihood composed of sequences of Bernoulli trials.

Full Likelihood Model

$$f(y_{FULL}|\Theta, R(t)) = g_S(y_S|R(t*)) \times \prod_{i=1}^{n_C} g_{C_i}(y_{C_i}|R_i(t*)) \times f_S(y_S|\Theta) \times \prod_{i=1}^{n_C} f_{C_i}(y_{C_i}|\Theta_i)$$

where $y_{FULL} = (y_S, y_{C_i}, x_S, n_s, x_{C_i}, n_{C_i}), \qquad i = 1, \ldots, n_c$.

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Extensions to Censoring

Censoring Type	Likelihood Contribution
Uncensored	$f_i(t\|\theta)$
Right Censored$(t > t_R)$	$1 - F_i(t_R\|\theta)$
Left Censored$(t < t_L)$	$F_i(t_L\|\theta)$
Interval Censored$(t_L \leq t \leq t_R)$	$F_i(t_R\|\theta) - F_i(t_L\|\theta)$

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Reparameterized Beta Distributions

- Experts often have an easier time specifying component reliability (π_i) and an associated *weight* or *worth* (η_i)

$$p(R_i) \quad \propto \quad R_i^{\pi_i \eta_i - 1}(1 - R_i)^{(1-\pi_i)\eta_i - 1}$$

where R_i is the unknown component reliability, π_i is the SME specified reliability and η_i is the equivalent "worth" or "weight" of the SME experience.

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- Example: Suppose a SME estimates the reliability to be 0.80 and additional SME's "value" her opinion as 8 component tests. Then, the prior would be specified as $\pi_i = 0.80$ and $\eta_i = 8$.

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- Hierarchical Prior:

$$\begin{aligned} \eta_i &\sim Gamma(\alpha, \beta) \\ \alpha &\sim Gamma(a_\alpha, b_\alpha) \\ \beta &\sim Gamma(a_\beta, b_\beta) \end{aligned}$$

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$$\pi_i \eta_i = \frac{(2/3)^{1/n_c} - 1}{1 - (4/3)^{1/n_c}}$$

$$(1-\pi_i)\eta_i = \pi_i \eta_i \frac{1 - (1/2)^{1/n_c}}{(1/2)^{1/n_c}} = \left(\frac{(2/3)^{1/n_c} - 1}{1 - (4/3)^{1/n_c}}\right)\left(\frac{1 - (1/2)^{1/n_c}}{(1/2)^{1/n_c}}\right)$$

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number of components	$\eta_i \pi_i$	$\eta_i(1-\pi_i)$
1	1.00	1.00
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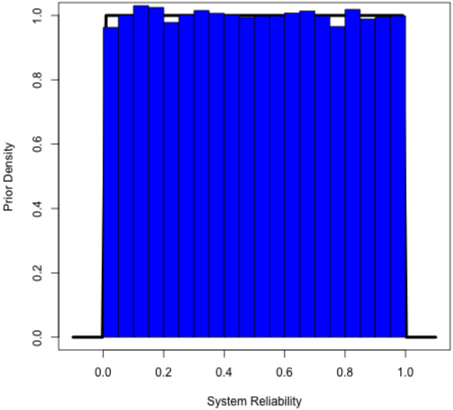
Graphical Illustration on Uniform Priors ($n_c = 2$)



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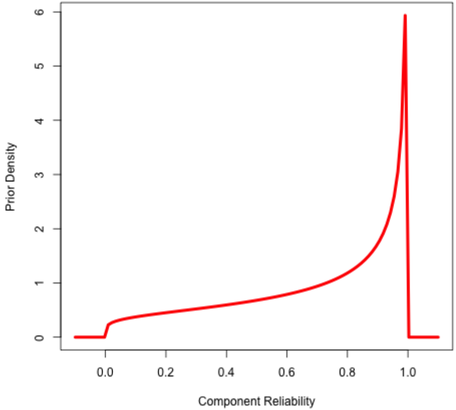
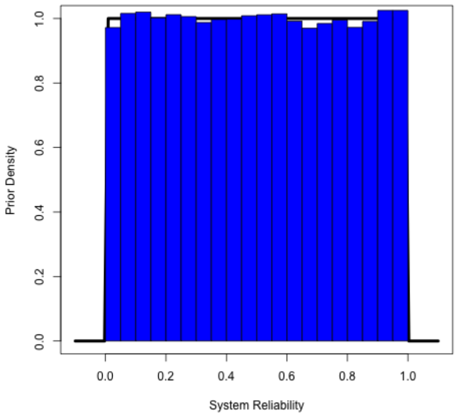


Graphical Illustration on Uniform Priors ($n_c = 7$)



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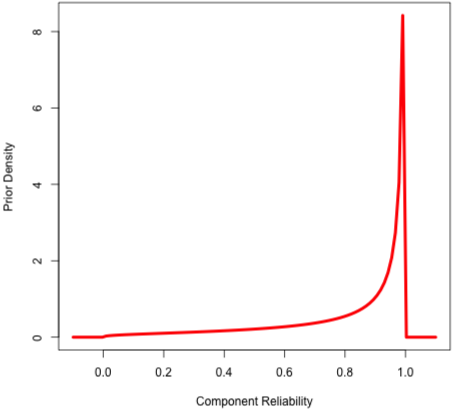

Incorporation of Historical Data: Commensurate Priors

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- Let D_0 be historical data with likelihood $L(D_0|\theta_0)$.
- Also, assume a vague initial prior for θ (either reliabilities, or parameters governing the reliability distribution), $\pi_0(\theta)$.
- Then, we can obtain the posterior distribution of θ through a hierarchical distributional specification:

$$\pi(\theta|D_0, \theta_0, \tau) \propto L(D_0|\theta_0)\pi(\theta|\theta_0, \tau)\pi_0(\theta)$$

Commensurability Parameter, τ

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  2. $\tau \longrightarrow \infty$ implies high commensurability ($\theta \equiv \theta_0$), and historical data are pooled as equal partners in posterior estimation.

Outline

Flight Test Data

Component	Tests	Failures
System	3	0
1	12	1
2	14	1
3	49	1
4	64	0
5	36	1
6	20	1
7	7	0

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- where v is the vibration until failure, and α and β are the shape and scale parameters of the Weibull distributions.

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- Borrowing from other systems using reparameterized Beta

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- Updates on logit scale accommodate very high (and very low!) reliabilities
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- No adaptation. Posterior may not be amenable. (Rosenthal, 2008)

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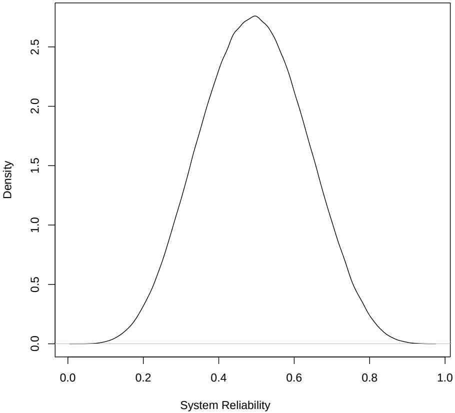
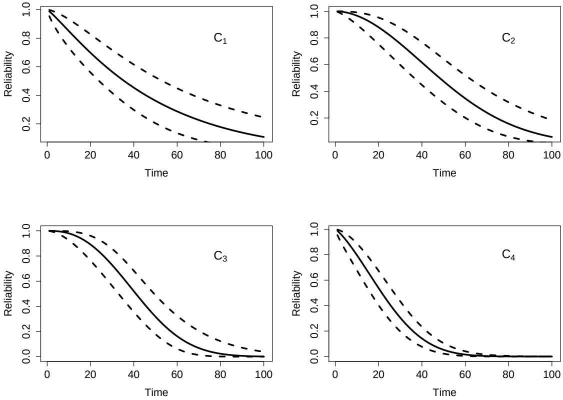
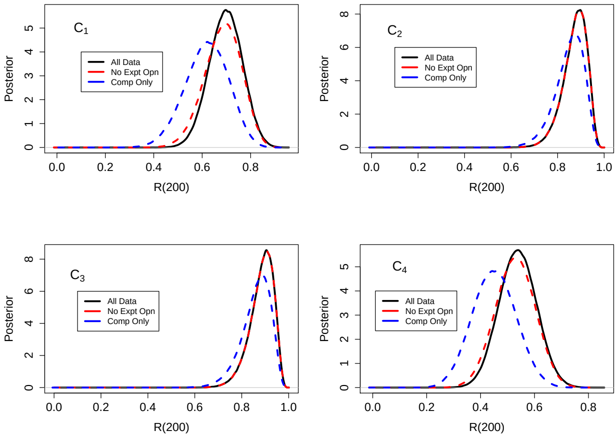
System Reliability



Reliability with all data incorporated



Comparison of Reliability Contribution



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- Nonparametric bayes does not assume rigid, parametric forms, but may require datasets that are too large for realistic implementation.

Conclusions

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  1. Biological systems?
  2. Complex Survey sampling – come to the clinical session!