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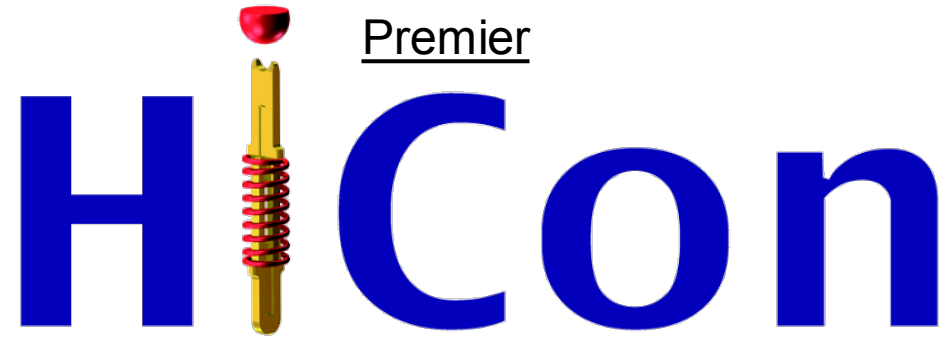
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Flexible Burn-In Sampling Plans

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Contents

- Burn-in (BI) Concepts
- BI Model approach
- BI Sampling Plans



Flexible Burn-In Sampling Plans

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BI Concepts

- Two major tools in QM
 - 100 % control
 - Sampling
- At BI
 - 100 % BI
 - Typically, BI time reductions
 - BI studies
 - Random sample to BI
 - As long as the random sample is not fully assessed → 100 % BI of the rest of the population
 - Once BI study is pass → BI monitoring



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BI Model Approach

- Limited failure population lifetime model

$$\pi_{(t,\infty)} = P(T_{ef} > t) \cdot \pi$$

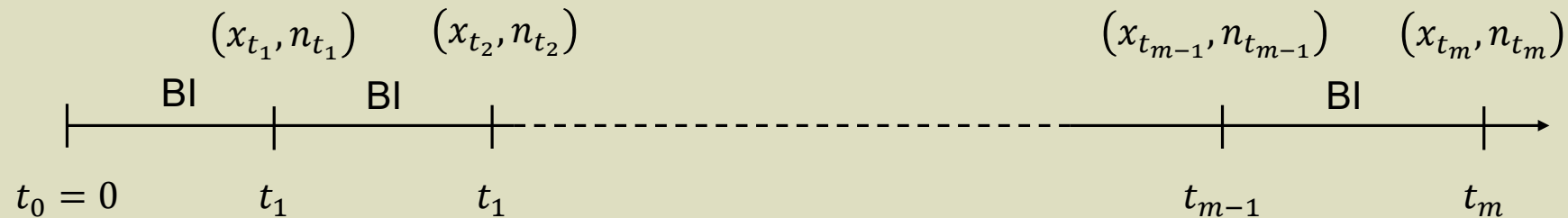
with

- π : probability of failures in the overall population
- $P(T_{ef} > t) = 1 - P(T_{ef} < t)$: probability of early failures after time t
 - \rightarrow knowledge about lifetime distribution of early failures is needed.
 - E.g., $T_{ef} \sim Weibull(3,0.5)$ (ReliaSoft).



Data Structure

- Interval censored data:



- $\mathbf{n}_t = (n_{t_1}, \dots, n_{t_m})$: vector of stressed devices at each BI time interval $(t_{j-1}, t_j]$, $j=1, \dots, m$;
- $\mathbf{x}_t = (x_{t_1}, \dots, x_{t_m})$: vector of BI failures at each BI time interval $(t_{j-1}, t_j]$, $j=1, \dots, m$;
- $\mathcal{S}(\mathbf{x}_t, \mathbf{n}_t)$: data from a BI study.

Estimation of Early Failure Probability

1. Calculate the likelihood function of π based on the data set $\mathcal{S} = \mathcal{S}(\mathbf{x}_t, \mathbf{n}_t)$.
2. Assign a prior distribution to π ensuring compliance with the Clopper-Pearson estimator.
3. Determine the posterior distribution of $\hat{\pi}$ and calculate its $(1 - \alpha)$ -quantile.

Likelihood Function

1. Calculate the likelihood function of π based on the data set

$$\mathcal{S} = \mathcal{S}(x_t, n_t).$$

– $n_{t_{j+1}}$ devices in the interval $(t_j, t_{j+1}]$ are a subset of the n_{t_j} devices in the interval $(t_{j-1}, t_j]$, $j = r + 1, \dots, m - 1$.

- → devices are not stochastically independent.
- → Likelihood function as product of conditional probabilities:

$$\mathcal{L}(\pi, \mathcal{S}) = \prod_{j=r+1}^m MN \left(\left(x_{t_j}, n_{t_j} - x_{t_j} \right)^T ; n_{t_j}; \left(\pi_{(t_{j-1}, t_j]}, 1 - \pi_{(t_{j-1}, t_j]} \right)^T \mid x_{t_r}, \dots, x_{t_{j-1}} = 0 \right).$$

Likelihood Function

2. Assign a prior distribution to π ensuring compliance with the Clopper-Pearson estimator.

– We set $\pi_{(t_r, t_m]} \sim Be(1, 0)$,

$$f(\pi_{(t_r, t_m]}) \propto \frac{1}{1 - \pi_{(t_r, t_m]}}.$$

– Needed: prior distribution function for π :

$$\pi_{(t_r, t_m]} = P(t_r < T_{ef} \leq t_r) \cdot \pi.$$

– Utilizing the change of variable theorem

$$f(\pi) \propto \frac{P(t_r < T_{ef} \leq t_r)}{1 - P(t_r < T_{ef} \leq t_r) \cdot \pi}.$$



Posterior Distribution

3. Determine the posterior distribution of $\hat{\pi}$ and calculate its $(1 - \alpha)$ -quantile.

- The posterior density $f(\pi|\mathcal{S})$ is calculated via Bayes' rule.
- Devices in the interval $(t_j, t_{j+1}]$ are a subset of the n_{t_j} devices in the interval $(t_{j-1}, t_j]$, $j = r + 1, \dots, m - 1$.
 - → devices are not stochastically independent.
 - → Likelihood function as product of conditional probabilities:

$$f(\pi|\mathcal{S}) = \frac{\mathcal{L}(\pi;\mathcal{S}) \cdot f(\pi)}{\int_0^1 \mathcal{L}(\pi;\mathcal{S}) \cdot f(\pi) \cdot \pi}$$

BI Sampling Plans

- $\mathbf{n}_t^{(t_i)} = (n_{t_1}^{(t_i)}, \dots, n_{t_m}^{(t_i)})$: vector of required numbers of passed devices after each readout time t_j in order to reduce the BI time from t_i to t_{i-1} .
- $\mathbf{x}_t^{(t_i)} = (x_{t_1}^{(t_i)}, \dots, x_{t_m}^{(t_i)})$: vector of possible failures in each interval $(t_{j-1}, t_j]$ before the BI time is reduced from t_i to t_{i-1} .
- $n_{t_1}^b$: planned number of devices that are put to BI for a batch with BI time t_i .
- Find vectors, such that

$$\left\{ \hat{\pi}_{(t_{i-1}, \infty)} \left(\mathcal{S} \left(\mathbf{0}_t, \mathbf{n}_t^{(t_i)} \right) \right) \leq \pi_{target} \right\} \text{ AND } \left\{ P \left(\hat{\pi}_{(t_{i-1}, \infty)} > \pi_{target}; \mathcal{S} \left(\mathbf{0}_t, \mathbf{n}_t^{(t_i)} \right) \right) \leq \gamma \right\}$$

Delaying Factor

- Probability to increase the BI time after a BI time reduction

$$P\left(\hat{\pi}_{(t_{i-1}, \infty)} > \pi_{target}; \mathcal{S}\left(\mathbf{0}_t, \mathbf{n}_t^{(t_i)}\right)\right)$$

$$= \sum_{j=1}^{i-1} P\left\{\hat{\pi}_{(t_{i-1}, \infty)} > \pi_{target}; \mathcal{S}\left(\mathbf{0}_t, \mathbf{n}_t^{(t_{j+1})}\right)\right\} \cdot P\left(\mathcal{S}\left(\mathbf{0}_t, \mathbf{n}_t^{(t_{j+1})}\right)\right)$$

with

$$P\left\{\hat{\pi}_{(t_{i-1}, \infty)} > \pi_{target}; \mathcal{S}\left(\mathbf{0}_t, \mathbf{n}_t^{(t_{j+1})}\right)\right\}$$

$$= \sum_{\mathbf{x}_t^{(t_j)}} I\left\{\hat{\pi}_{(t_{i-1}, \infty)}\left(\mathcal{S}\left(\mathbf{x}_t^{(t_j)}, \mathbf{n}_t^{(t_j)}\right)\right) > \pi_{target}\right\} \cdot P\left(\mathbf{X}_t^{(t_j)} = \mathbf{x}_t^{(t_j)}; \mathcal{S}\left(\mathbf{0}_t, \mathbf{n}_t^{(t_{j+1})}\right)\right)$$

BI Time Reduction Strategies

Reduction Strategy	BI time	$(0, t_1]$	$(t_1, t_2]$	$(t_2, t_3]$
R_1	t_3	i	i	i
	t_2	ii	ii	
	t_1	iii		
R_2	t_3	ii	i	i
	t_2	ii	ii	
	t_1	iii		
R_3	t_3	iii	i	i
	t_2	iii	ii	
	t_1	iii		
R_4	t_3	iii	ii	i
	t_2	iii	ii	
	t_1	iii		



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BI Time Reduction Strategy - Example

- Reduction Strategy R_1
 - Acceptance criterion: 0 failures.
 - Reduction to t_2 : the intervals $(t_0, t_1]$, $(t_1, t_2]$, and $(t_2, t_3]$ are analyzed.
 - Reduction to t_1 : the intervals $(t_0, t_1]$ and $(t_1, t_2]$ are analyzed.

$$- \left(x_t^{(t_j)}, n_t^{(t_j)} \right) = \begin{cases} \left(\left(x_{t_1}^{(t_3)}, x_{t_2}^{(t_3)}, x_{t_3}^{(t_3)} \right), \left(n_{t_3}^b, n_{t_3}^b, n_{t_3}^b \right) \right) & i = 3 \\ \left(\left(x_{t_1}^{(t_2)}, x_{t_2}^{(t_2)}, 0 \right), \left(n_{t_2}^b + n_{t_3}^b, n_{t_2}^b + n_{t_3}^b, n_{t_3}^b \right) \right) & i = 2 \\ \left(\left(x_{t_1}^{(t_1)}, 0, 0 \right), \left(n_{t_1}^b + n_{t_2}^b + n_{t_3}^b, n_{t_2}^b + n_{t_3}^b, n_{t_3}^b \right) \right) & i = 1 \end{cases}$$

BI Time Reduction Strategy - Example

- Reduction Strategy R_1 (cont.)

$$P \left(\mathbf{x}_t^{(t_j)}, \mathbf{n}_t^{(t_j)} \right)$$

$$= \begin{cases}
 \left[\text{NMN} \left(\left(\mathbf{x}_{t_1}^{(t_3)}, \mathbf{x}_{t_2}^{(t_3)}, \mathbf{x}_{t_3}^{(t_3)}, n_{t_3}^b - \sum_{j=1}^3 x_{t_j}^{(t_3)} \right)^\top, n_{t_3}^b, (\hat{\pi}_{(0,t_1]}, \hat{\pi}_{(t_1,t_2]}, \hat{\pi}_{(t_2,t_3]}, 1 - \hat{\pi}_{(0,t_3]})^\top \right) \right] & i = 3 \\
 \left[\text{NMN} \left(\left(\mathbf{x}_{t_1}^{(t_2)}, \mathbf{x}_{t_2}^{(t_2)}, n_{t_2}^b + n_{t_3}^b - \sum_{j=1}^2 x_{t_j}^{(t_2)} \right)^\top, n_{t_2}^b + n_{t_3}^b, (\hat{\pi}_{(0,t_1]}, \hat{\pi}_{(t_1,t_2]}, 1 - \hat{\pi}_{(0,t_2]})^\top \right) \right] & i = 2 \\
 \left[\text{NB} \left(\mathbf{x}_{t_1}^{(t_1)}, n_{t_1}^b + n_{t_2}^b + n_{t_3}^b, \hat{\pi}_{(0,t_1]} \right) \right] & i = 1
 \end{cases}$$



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Case Study

- Initial Sampling Plan
 - Readout times:
 - $t_1 = 7$ h,
 - $t_2 = 19$ h,
 - $t_3 = 48$ h.
 - Quality target:
 - 25 ppm @ 90 % CL.
 - Delaying factor:
 - 10 %.

Reduction Strategy	BI time	(0, 7 h]	(7 h, 19 h]	(19 h, 48 h]
R_1	48 h	0/13 k	0/13 k	0/13 k
	19 h	0/36.4 k	0/36.4 k	
	7 h	0/110.3 k		
R_2	48 h	x/62.4 k	0/62.4 k	0/62.4 k
	19 h	0/62.4 k	0/62.4 k	
	7 h	0/101.8 k		
R_3	48 h	x/69.3 k	0/69.3 k	0/69.3 k
	19 h	x/207.4 k	0/207.4 k	
	7 h	0/207.4 k		
R_4	48 h	x/211.2 k	x/211.2 k	0/211.2 k
	19 h	x/211.2 k	0/211.2 k	
	7 h	0/211.2 k		



Case Study

- Deviations at the 1st readout

Reduction Strategy	BI time	(0, 7 h]	(7 h, 19 h]	(19 h, 48 h]
R_1	48 h	1-3/14 k	0/13.5 k	0/13 k

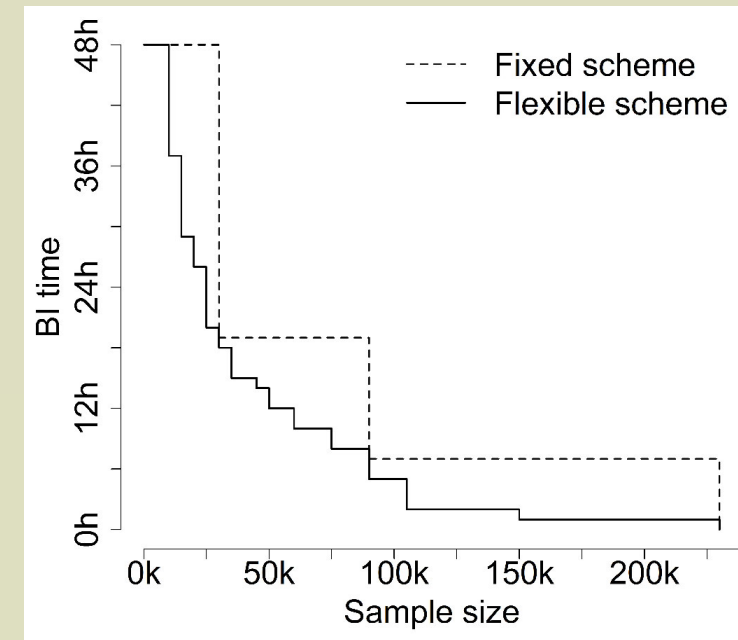
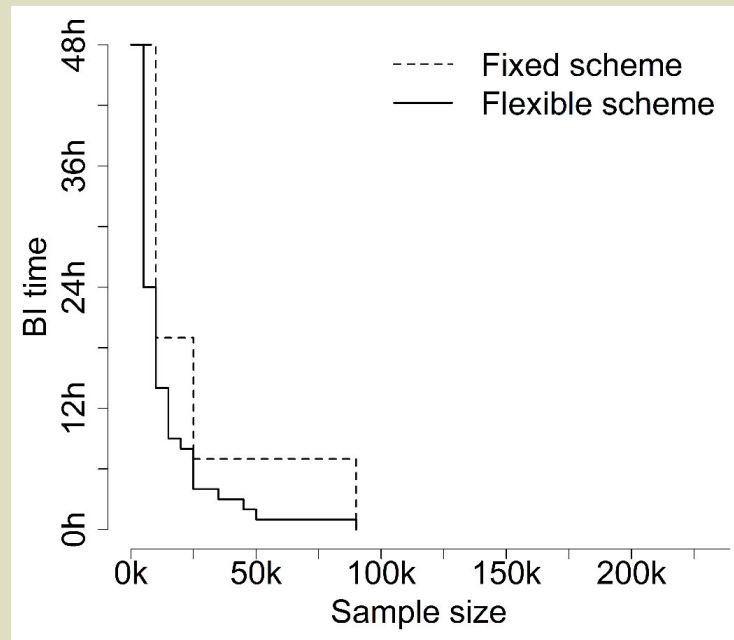
- Update of the sampling plan:

$$\left(t, n_t^{(t_j)} \right) = \begin{cases} ((7 h, 19 h, 26 h), (110.8 k, 36.9 k, 13.5 k)) & \text{for } x_{t_1}^{(t_3)} = 1 \\ ((7 h, 19 h, 30 h), (110.6 k, 36.7 k, 13.3 k)) & \text{for } x_{t_1}^{(t_3)} = 2 \\ ((7 h, 19 h, 34 h), (110.5 k, 36.6 k, 13.2 k)) & \text{for } x_{t_1}^{(t_3)} = 3 \end{cases}$$

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Case Study

- Follower products
 - Area product A: 0.5 x reference product
 - Area product B: 2.0 x reference product



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Reference

- Kurz, D, Lewitschnig, H, Pilz, J. Flexible time reduction method for burn-in of high-quality products. *Qual Reliab Eng Int.* 2021; 37: 2900– 2915.