

Simple Bayesian Updating by Cross-Entropy Minimization: Application at Leibstadt NPP

Jan Kasperek

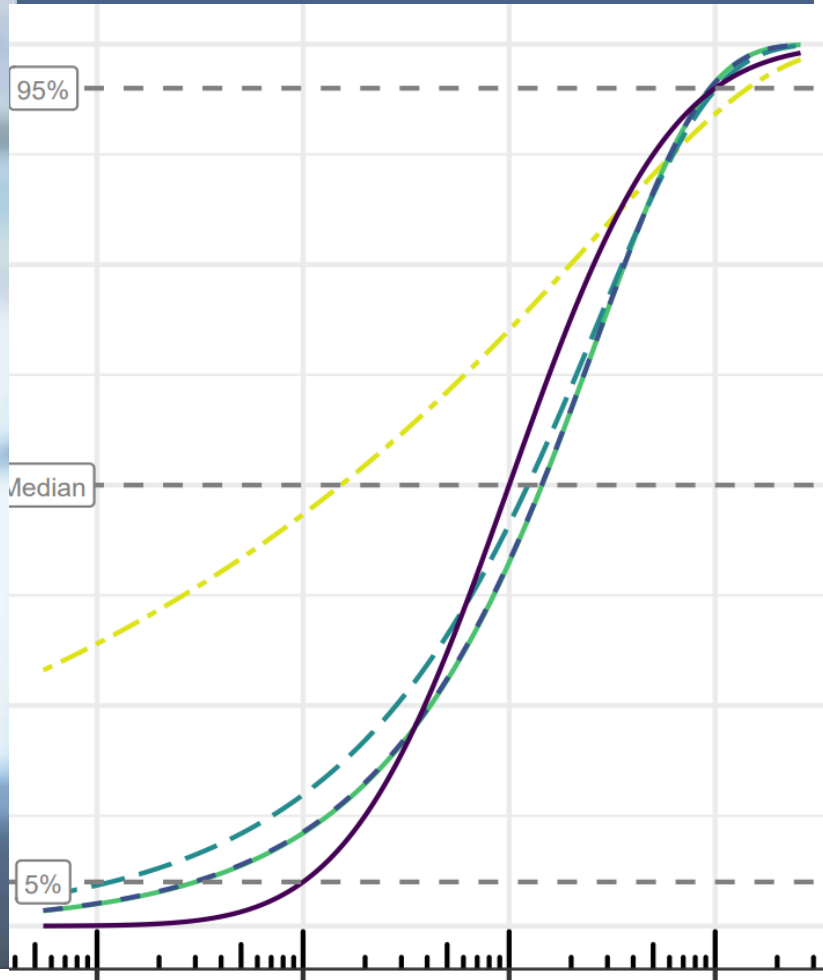
**Department of Nuclear Safety
Leibstadt Nuclear Power Plant
Switzerland**

PSAM 18

July 19-July 24, 2026, Pittsburgh PA



Simple Bayesian Updating by Cross-Entropy Minimization



Outline

1. Background & Motivation
2. Theory: Development of New Approach
3. Evaluation
4. KKL PSA Application
5. Extensions & Other Uses

Bayesian Updating for Leibstadt NPP (KKL) PSA: Background & Motivation

- Purpose: Combine quantitative information from different sources in a systematic way
 - Generic industry data + plant-specific evidence
 - Taking into account the associated uncertainties
 - Obtaining actual probability distributions as a result (as opposed to point estimates & confidence intervals)
- Swiss PSA regulation ENSI-A05 requires Bayesian Updating for:
 - Component Reliability Data: Failure Rates, CCF Parameters
 - Internal Plant Hazards: Frequencies of Internal Fire & Internal Flooding
 - Internal Initiating Events: Frequencies of Transients & LOCAs
- Practical challenges:
 - Generic Distributions in (KKL) PSA often not conjugate → numerical methods
 - Numerical instabilities
 - Transparency: Bayesian Update becomes a «black box»
 - Software dependence → code maintenance, accessibility to all analysts, IT restrictions,.....

Theory: Development of New Approach

Simplified Method: Fitting Conjugate Priors to Generic Distributions

- **Well-known**: «*Moment Matching*»
- Equating first and second moments of generic distribution (density f) and conjugate prior (density g):
 - $\int \theta f(\theta) d\theta = \int \theta g(\theta) d\theta$
 - $\int \theta^2 f(\theta) d\theta = \int \theta^2 g(\theta) d\theta$

Equivalent to matching mean and variance

- **Proposed**: *Minimize Kullback-Leibler Divergence (KLD) & Cross-Entropy (such that generic mean is retained)*

$$\begin{aligned} D_{KL}(f \parallel g) &= \int_{\Omega} f(\theta) \cdot \ln\left(\frac{f(\theta)}{g(\theta)}\right) d\theta \\ &= \int_{\Omega} f(\theta) \cdot \ln(f(\theta)) d\theta - \int_{\Omega} f(\theta) \cdot \ln(g(\theta)) d\theta \end{aligned}$$

→ e.g., Optimization problem for Gamma distribution (density g):

$$\begin{aligned} &\max_{\alpha, \beta} \int_0^{\infty} f(\theta) \ln(g_{\alpha, \beta}(\theta)) d\theta \\ &\text{such that } \text{Mean}_{\text{generic}} = \frac{\alpha}{\beta} \end{aligned}$$

Gives large weight to differences in distribution tails

More robust to differences in tail behavior

Approximate Cross-Entropy Minimization to obtain Gamma Priors

▪ Continuous Generic Distributions (General Case)

- Requires continuous distribution with support on subset of $[0, \infty)$
- *Exact* cross-entropy minimization: Numerically solve

$$\ln(\alpha) - \psi_0(\alpha) \stackrel{!}{=} \ln(\mathbb{E}_f(\theta)) - \mathbb{E}_f(\ln(\theta))$$

- Define

$$\Delta = \ln(\mathbb{E}_f(\theta)) - \mathbb{E}_f(\ln(\theta))$$

- Bounds for shape parameter α :

$$\frac{1}{2\Delta} < \alpha < \frac{1}{\Delta}$$

- Optimal α converges to lower bound as $\Delta \rightarrow 0$
→ works well for small Δ
- Refined Approximation for large Δ :

$$\tilde{\alpha} = \frac{\Delta + 1.55}{\Delta^2 + 3.1\Delta}$$

▪ Lognormal Generic Distributions

- usual case in (KKL) PSA
- General Bounds become:

$$\frac{2.7}{\ln^2(EF)} < \alpha < \frac{5.4}{\ln^2(EF)}$$

- Lower bound within 19% of numerical solution for $EF \leq 10$

- Refined approximation for large EF :

$$\tilde{\alpha} = \frac{5.4\ln^2(EF) + 45}{\ln^4(EF) + 17\ln^2(EF)}$$

- Within 4% of numerical solution for $EF \leq 100$

After obtaining α , calculate the rate parameter

$$\beta = \alpha / \text{Mean}_{\text{generic}}$$

→ generic mean always retained

Equivalence to Maximum Likelihood

- Maximum Likelihood Estimation to fit Gamma distribution on observational data:

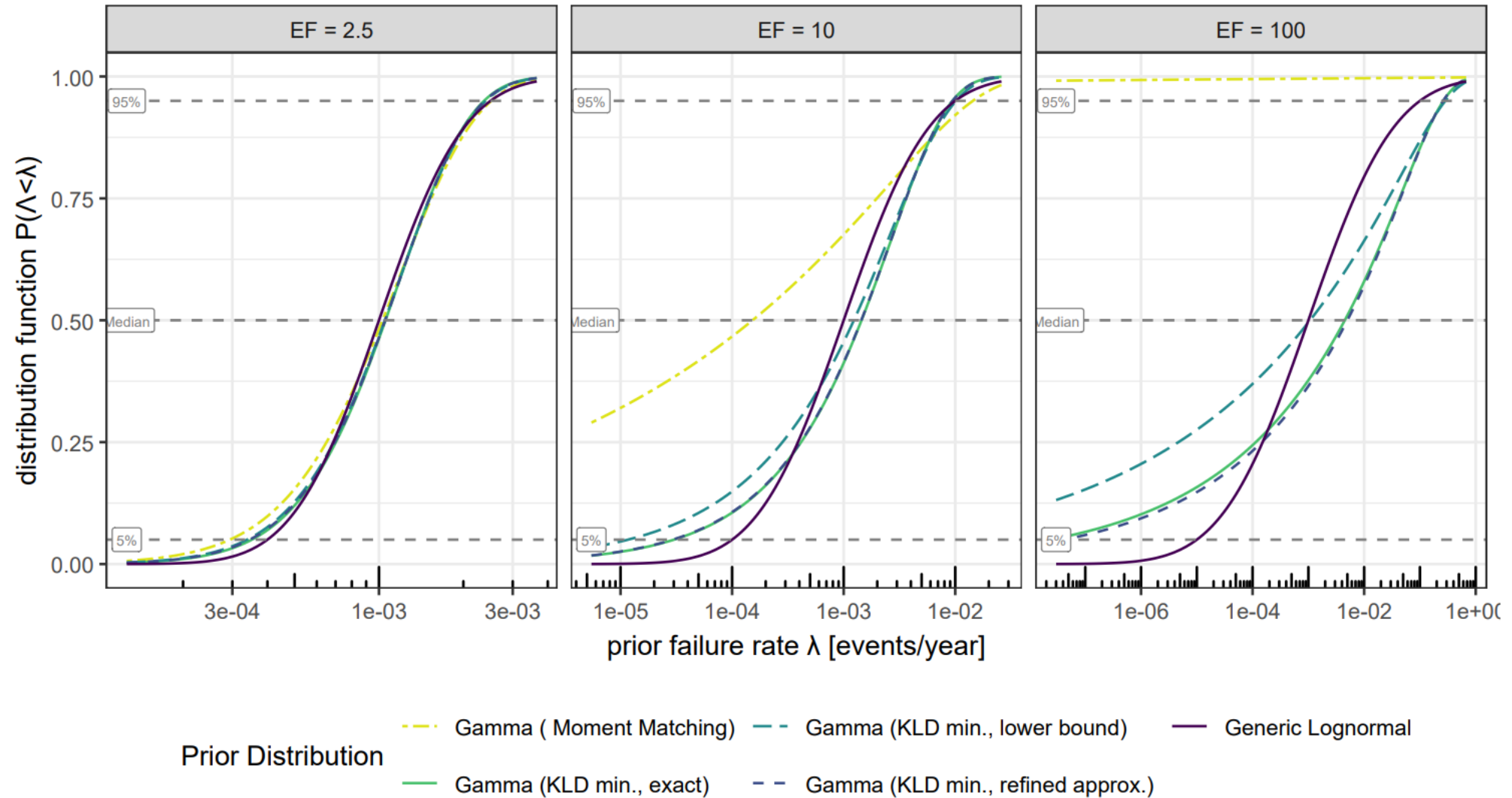
$$\ln(\alpha) - \psi_0(\alpha) \stackrel{!}{=} \ln\left(\frac{1}{n} \sum_{i=1}^n x_i\right) - \frac{1}{n} \sum_{i=1}^n \ln(x_i)$$

- Cross-Entropy Minimization to obtain approximate Gamma distribution:

$$\ln(\alpha) - \psi_0(\alpha) \stackrel{!}{=} \ln(\mathbb{E}_f(\theta)) - \mathbb{E}_f(\ln(\theta))$$

Evaluation: Generic Lognormal Distributions

Accuracy of Approximating Gamma Distributions



Comparison of *Posteriors* - Example from NUREG/CR-6823, Sec. 6.2.2.7.2: (Lognormal Prior: Median=1/1000, EF=10 & 0 events in 2102 exposure years)

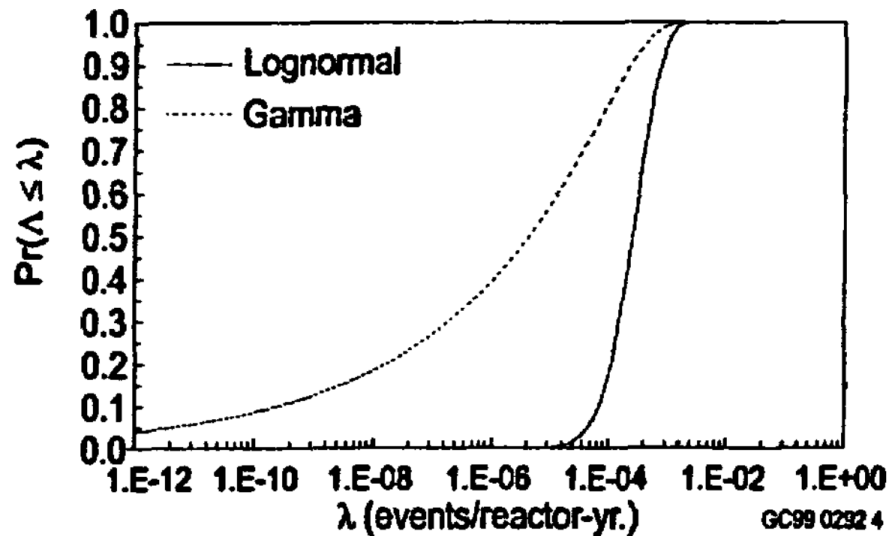
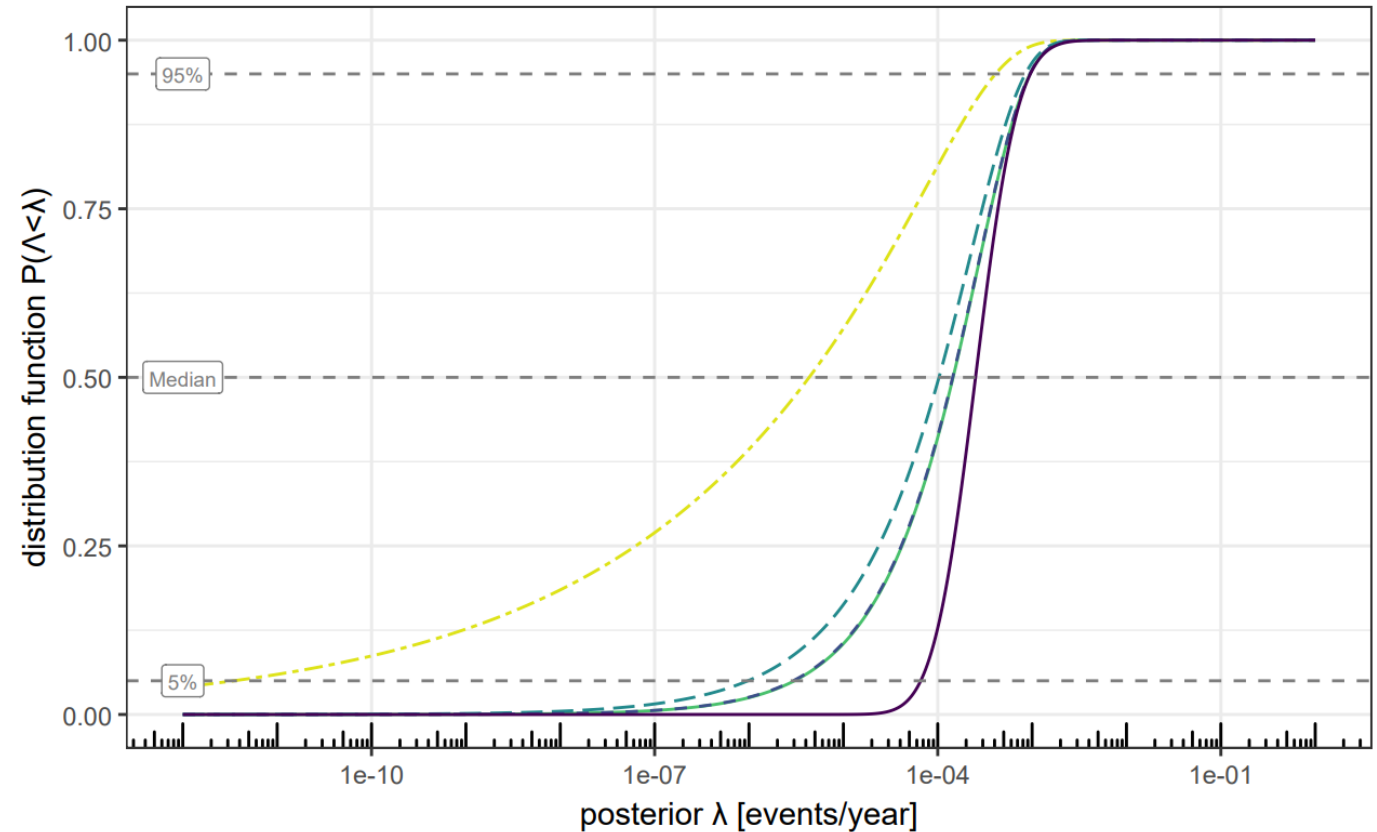


Figure 6.20 The same posterior distributions as in the previous figure, with λ plotted on logarithmic scale.



Posterior

- Gamma (Moment Matching)
- Gamma (KLD min., lower bound)
- Numerical
- Gamma (KLD min., exact)
- Gamma (KLD min., refined approx.)

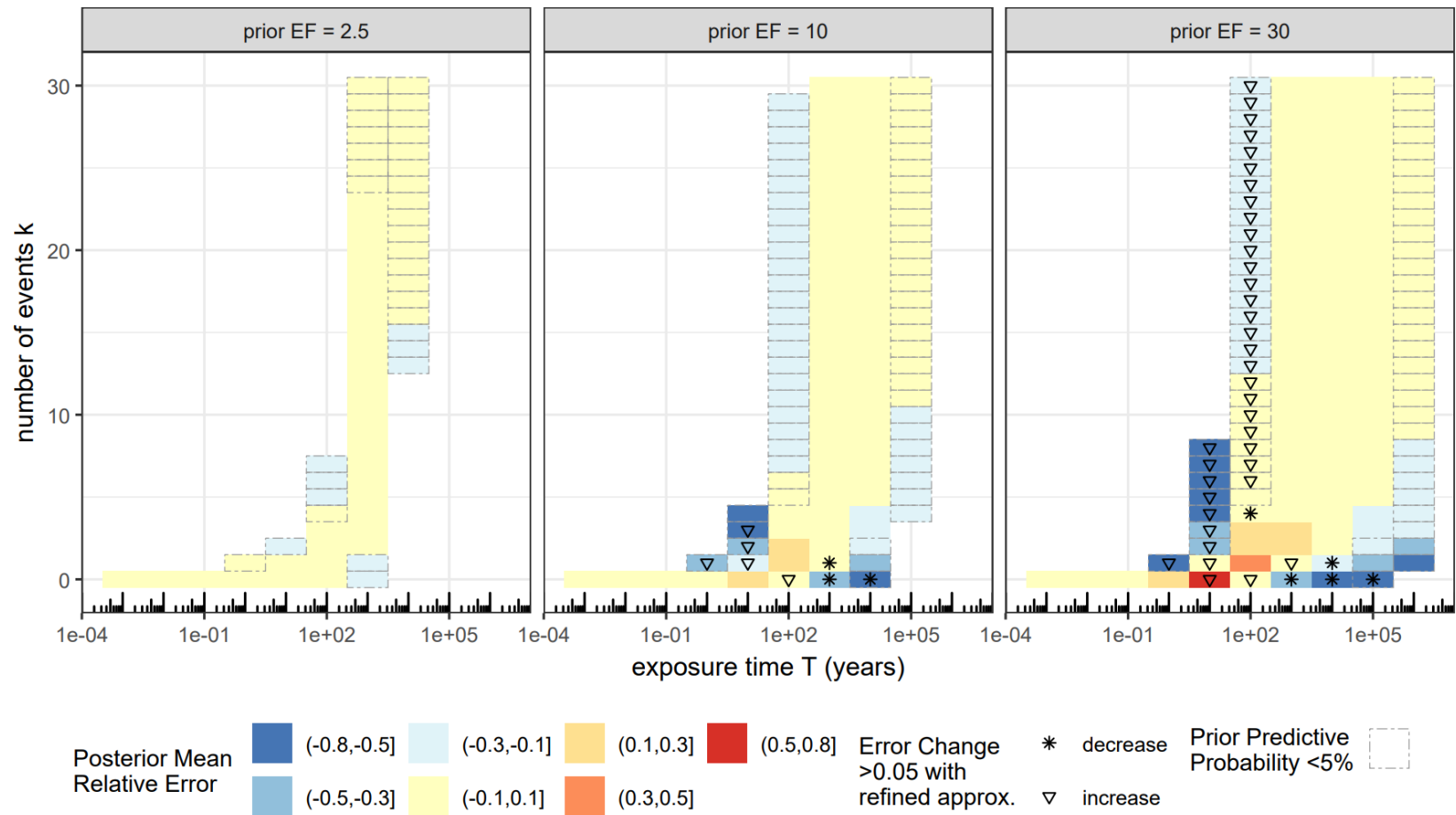
General Properties of Posteriors: Evaluation on Synthetic Data

- Synthetic data – constructed from realistic ranges for KKL PSA applications
 - Lognormal «Generic Data»
 - Mean = 1/100 events per year of exposure
 - Accuracy of Gamma approximation to lognormal depends only on the error factor
 - EF = {2.5, 10, 30}
 - Plant-Specific «Experience»
 - $k = \{0, 1, 2, \dots, 30\}$ events
 - $\text{Log}_{10}(T) = \{-3, -2, -1, \dots, 6\}$, exposure time T in years
- Create a grid of all combinations between generic parameters and evidence
- Filter out combinations which are extremely unlikely → prior-data consistency check
 - *Prior Predictive Distribution* (for Poisson Likelihood): Under the prior and statistical model assumed for plant data, what is the probability of observing exactly k events within exposure time T?

$$\mathbb{P}_{\text{ppd}}(K = k) = \int_0^{\infty} \mathbb{P}(K = k) f_{\text{gen}}(\lambda) d\lambda$$

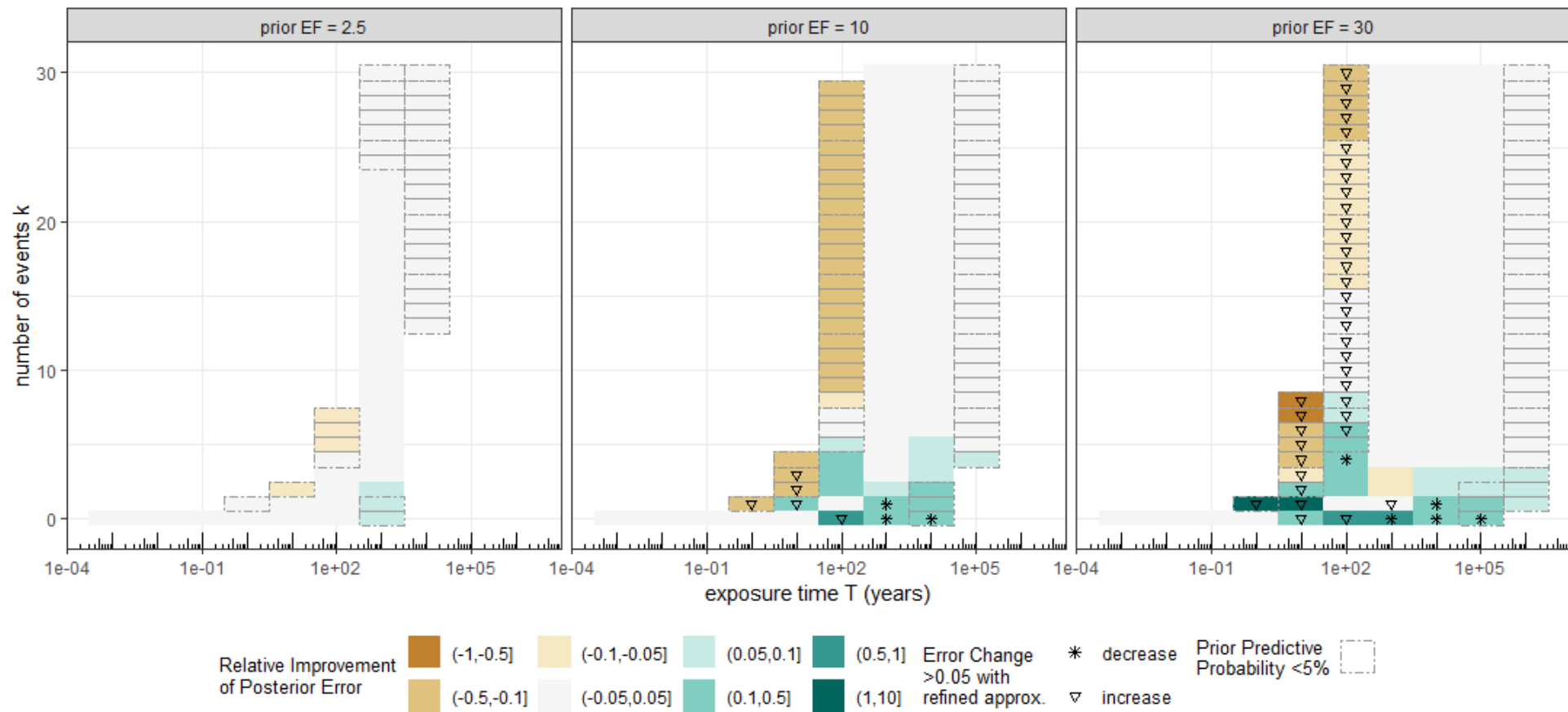
- Filter out combination if $\mathbb{P}_{\text{ppd}}(K \leq k) = \sum_0^k \mathbb{P}_{\text{ppd}}(K = k)$ or $\mathbb{P}_{\text{ppd}}(K \geq k) = 1 - \sum_0^{k-1} \mathbb{P}_{\text{ppd}}(K = k)$ is smaller than 1/1000

Approximate Cross-Entropy Minimization vs Numerical Updating: Posterior Mean Relative Error



< 10% Change in Posterior Means (more conservative for small k & T , less conservative in case of prior-data conflict)

Approximate Cross-Entropy Minimization vs Moment Matching: Comparison of Posterior Mean Relative Error



▶ Cross-Entropy Min. gives lower / similar Posterior Mean Error (unless event count is inconsistently high vs Generic Data)

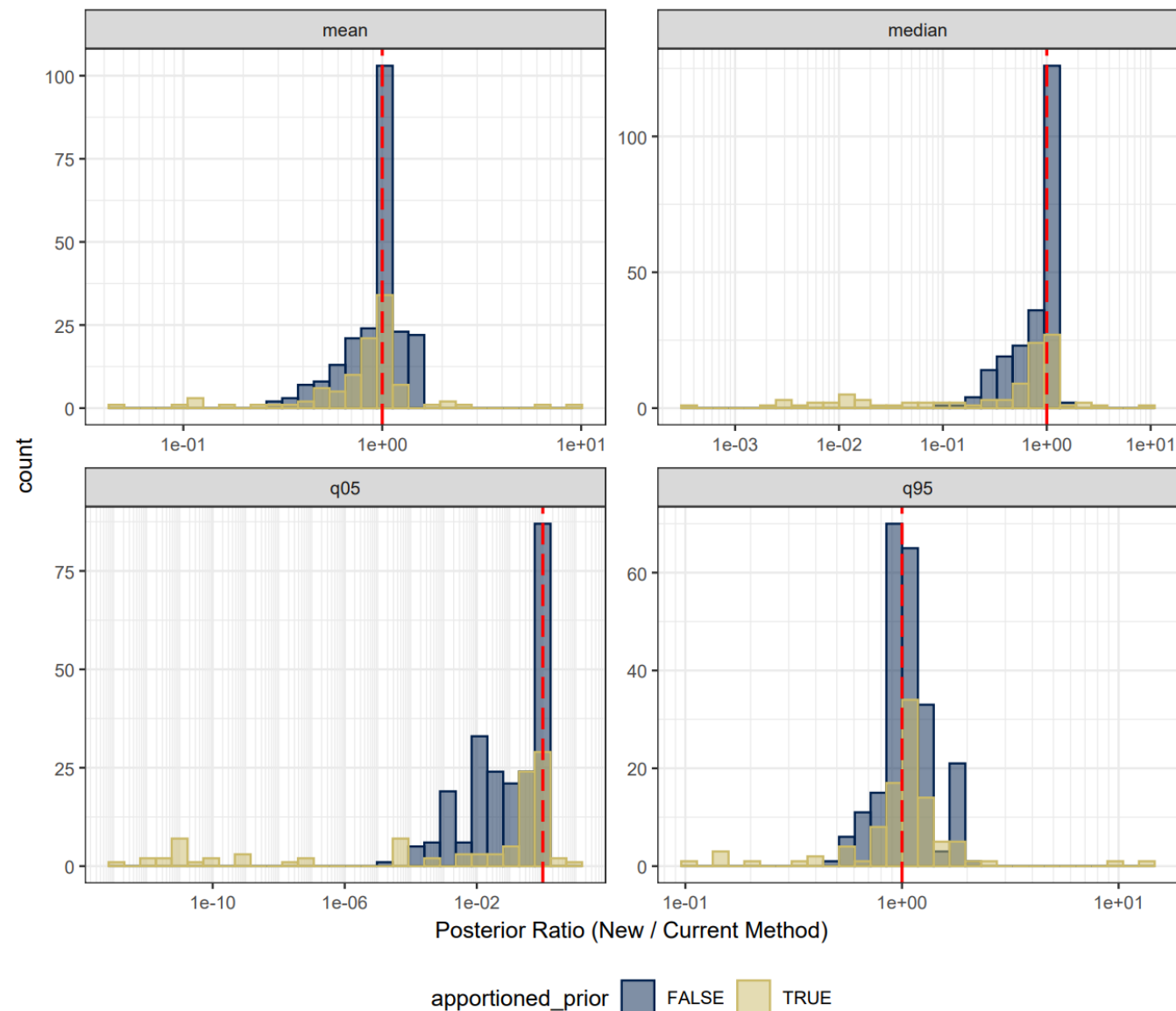
Similar pattern for 5th and 95th Posterior Percentiles (see paper)

KKL PSA Application

KKL PSA Application: Component Failure Rates

- KKL PSA Failure Rates:
 - On average, 2.5% decrease in Posterior Mean (q05: -60%, q95: +45%)
 - Order of magnitude changes in 5th Percentiles for 44% of components (mostly decreases)
 - Similar 95th Percentiles: on average +14% change (order of magnitude changes for 0.3% of components)
→ larger changes observed when using Moment Matching
- Core Damage Frequency:
 - Fully integrated PSA model; all plant operating states and internal & external initiators
 - Replaced numerically calculated mean failure rates with approximate cross-entropy minimization (lower bound of α)
→ **+ 3.7% in total mean core damage frequency**
- Differences between new and old failure rates due to 2 effects:
 - Bayesian Updating
 - Preprocessing of prior distributions due to different component boundaries in generic data vs KKL PSA
 - «Apportioning»: Splitting prior failure rates between sub-components
→ *Previously: Inexact apportioning by retaining the generic distribution type (→ 2014 IAEA IPSART mission comment)*
→ *Gamma Distribution: Exact Apportioning due to* $\lambda_i \sim \text{Gamma}(\alpha_i, \beta) \implies \sum_{i=1}^n \lambda_i \sim \text{Gamma}\left(\sum_{i=1}^n \alpha_i, \beta\right)$

Posterior Differences & «Apportioning»



Extensions & Other Uses

Other Generic Distributions & Likelihoods

Generic Distribution Types other than Lognormal

- Calculate $\Delta = \ln(\mathbb{E}_f(\theta)) - \mathbb{E}_f(\ln(\theta))$ for different generic distribution types to approximate them with Gamma distributions
 - Possible for distributions without support on $(-\infty, 0)$
 - Beta, Log-Uniform, Uniform,

Binomial Likelihood (Probability Parameter)

- Conjugate Prior: Beta Distribution
 - If event probabilities are small, Gamma distributions are well-approximated by Beta distributions
- ➔
1. Convert Generic Distribution into Gamma
 2. Convert resulting Gamma Distribution into Beta

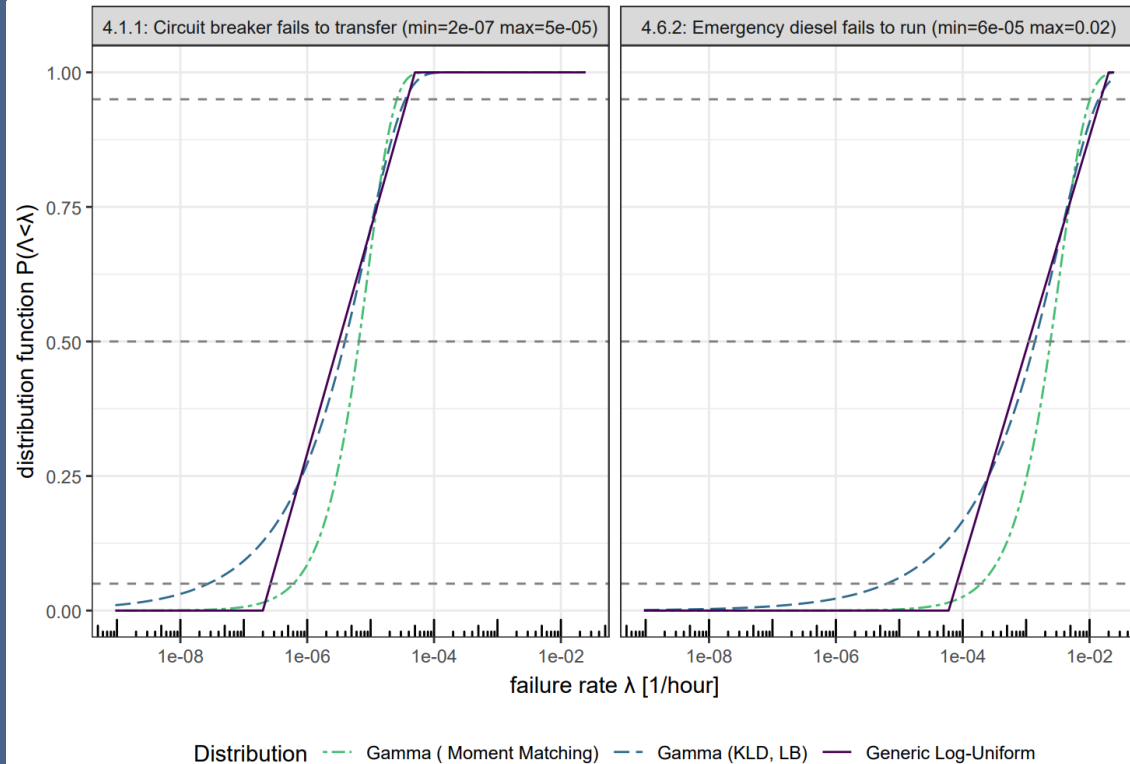
Table 1: Conversion of Common Generic Distributions into Conjugate Priors



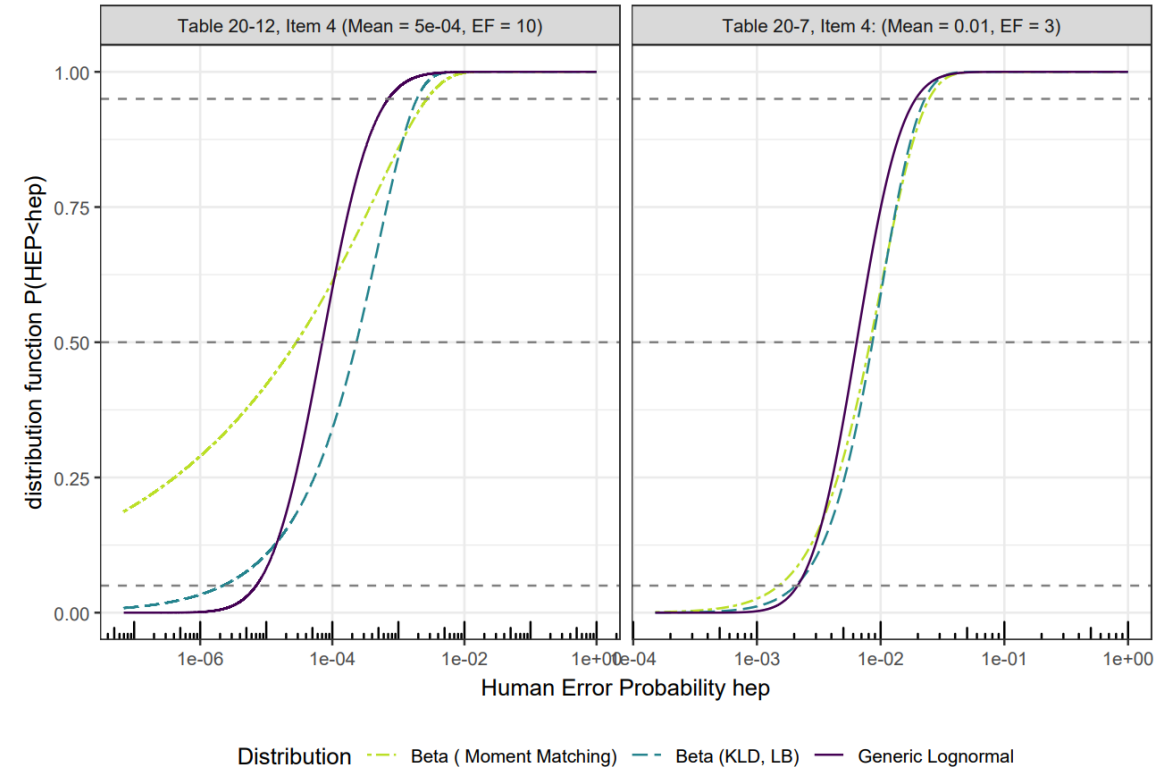
Generic Prior	Likelihood	(First) Shape Parameter, Lower Bound	Remark
$Beta(\varrho, \xi)$	Poisson	ϱ	mismatch of support & units
$Gamma(\alpha, \beta)$	Binomial	α	mismatch of support & units
$LogNormal(Mean, EF)$	Poisson	$2.7/\ln^2(EF)$	for large EF, see Equation 10
$LogNormal(Mean, EF)$	Binomial	$2.7/\ln^2(EF)$	mismatch of support & units
$LogUniform(a, b), 0 < a < b \leq 1$	Binomial	$1/(2\ln(b-a) - 2\ln(\ln(b/a)) - \ln(a) - \ln(b))$	mismatch of support
$LogUniform(a, b), 0 < a < b$	Poisson	$1/(2\ln(b-a) - 2\ln(\ln(b/a)) - \ln(a) - \ln(b))$	mismatch of support

Other Conversions: Examples

- Log-Uniform Failure Rates (from NUREG/CR-2815)



- Lognormal Human Error Probabilities (NUREG/CR-1278)



Further Applications

- Converting Lognormal probability parameters into Beta distributions
 - Matching the bounds for probabilities
 - E.g., Human Error Probabilities in HRA
- Kullback-Leibler divergence as measure for «information gain» from plant experience
 - KKL PSA: Supplements Prior Predictive Probabilities for prior vs data consistency checks (component failure rates)
 - Both criteria have closed-form expressions / approximations due to using Gamma priors

Thank You!

Jan Kasperek

✉ Jan.t.Kasperek@kkf.ch

☎ +41 56 267 8511

Department of Nuclear Safety
Leibstadt Nuclear Power Plant

Questions?

