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Simulator data and HRA models: accounting for variability

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Outline

- Why HRA models shall represents variability and how this is reflected in use of data from simulator
- Examples on artificial data
- Ongoing and future work

Why model variability

- HRA models provide Human Error Probabilities (HEPs) for types of tasks, influence factors, characterizations of context
  - E.g. SPAR-H: “diagnosis task”, “adequate time available”, “poor procedures” …
  - Address **categories** of task types, factor influences
  - There is **variability within these categories**, e.g. different realizations of how procedures may be “poor”
  - There is also **variability of crew** performances, behaviors, strategies

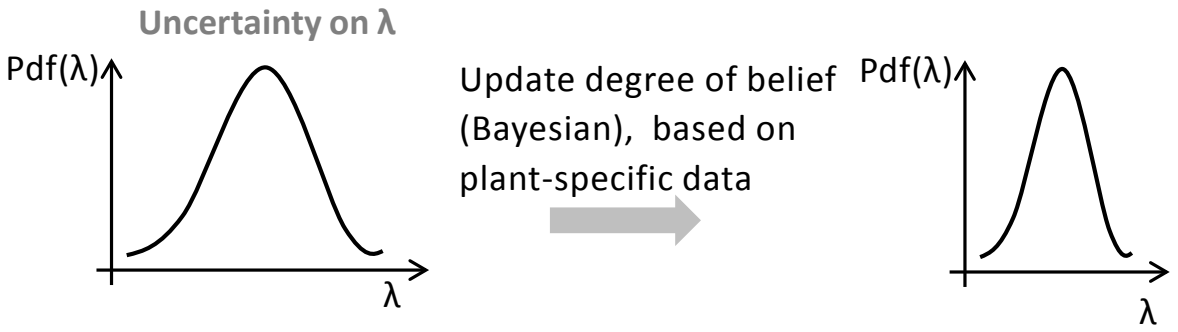
- **Simulator data** in general relates to **specific tasks** by a limited set of operating crews, e.g. LOCA of given size, HPI failed, given procedural guidance,…

- We investigated a model to explicitly treat these two sources of variability
  - **Within-PSF** (performance shaping factors) variability
  - **Crew variability**

Uncertainty and variability

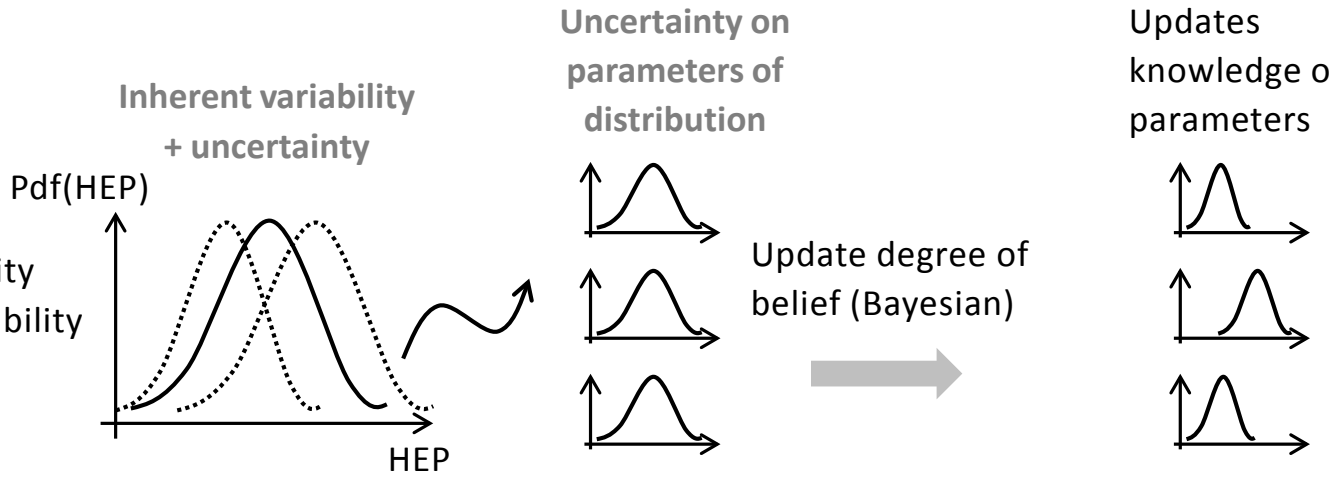
- Typical approach in probabilistic safety assessment, e.g. λ failure rate of pump

- Lack of knowledge
- Plant-to-plant variability (operating conditions, quality of maintenance)
- Specific type of component (vendor, model)



- In HRA, human error probabilities assessed based on models; HEP inherently variable
  - Person- team- variability
  - Variability within ratings of PSFs (e.g. 'adequate procedures' envelops various cases)

- Lack of knowledge
- Within-PSF variability
- Person- team- variability
- …



HEP for a specific task type, specific set of PSFs

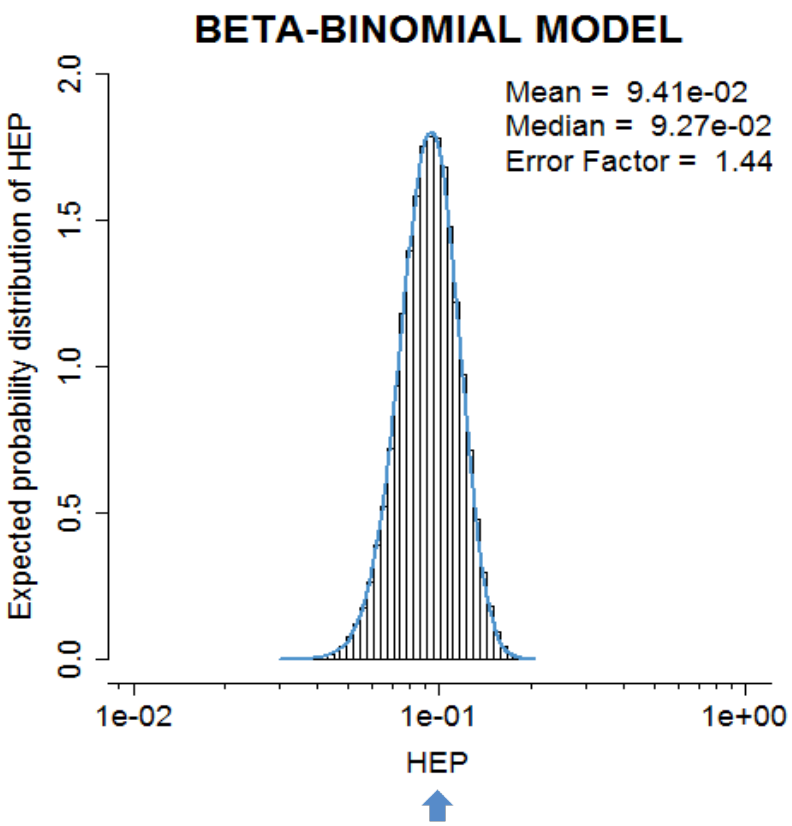
Two approaches:

APPROACH	HYPOTHESES	VARIABLES	BAYESIAN INFERENCE MODEL
Beta-Binomial	Unique HEP value associated to the same type of task, same set of PSFs Within-task, -PSF and crew variability represented by the probability itself	1 variable HEP	Beta prior (α=1,β=1) → HEP → Binomial aleatory model ← k_{TOT}, N_{TOT} ← Evidence (single piece) $\pi(HEP_{PSF}\|\alpha_{post},\beta_{post},E)$ = post. predictive $\alpha_{post} = \alpha_{prior} + k_{tot}$ $\beta_{post} = \beta_{prior} + N_{tot}$
Variability model	HEP distribution associated to the same type of task, same set of PSFs A unique HEP value is associated to a specific task and scenario context, performed by a specific crew - Hierarchical model (two-stages), assuming lognormal var. functions	2 continuous variables μ_t $\sigma = f(\sigma_t,\sigma_c)$	Hyper-parameters → μ_t, σ → Lognormal prior (μ_t, σ) → HEP_t → Binomial aleatory model ← k, N ← Evidence $\pi(HEP_{PSF}\|\mu_t,\sigma,E)$ = post. predictive $\pi(\mu_t\|E)$ = post. distribution of μ_t $\pi(\sigma\|E)$ = post. distribution of σ

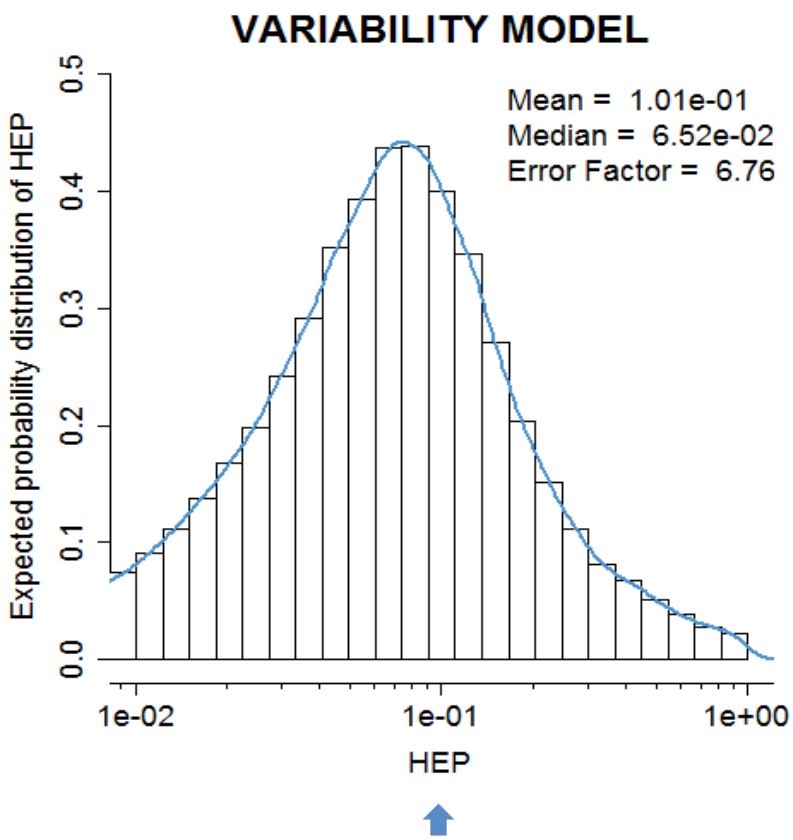
Effect of consideration of variability

- Hypothetical data on number of failures for **a specific task type, specific set of PSFs**
  - 20 tasks (N_{task}), 10 repetitions (N_{rep}) of task by the same crew

of failures on 10 repetitions
3
1
3
1
0
1
1
3
0
1
0
0
0
2
0
0
0
0
2
3



A unique value of HEP associated to task type and set of PSFs, subject to uncertainty

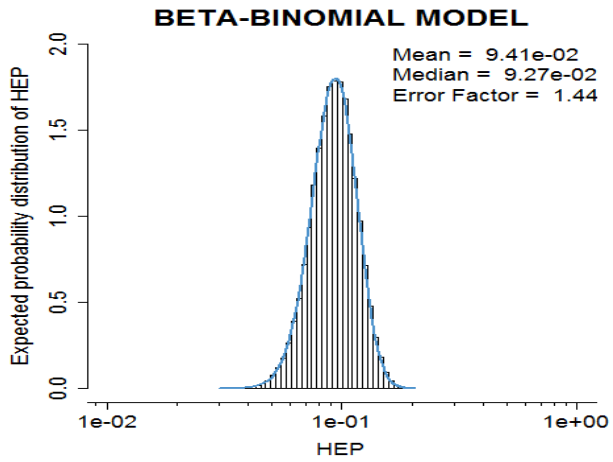


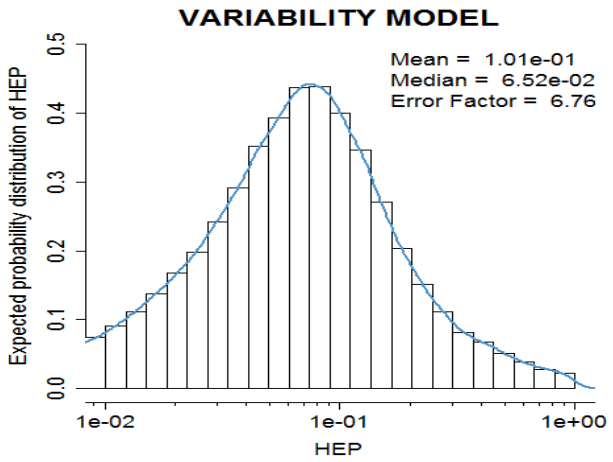
A distribution of HEP associated to task type and set of PSFs, with parameters subject to uncertainty

Effect of consideration of variability

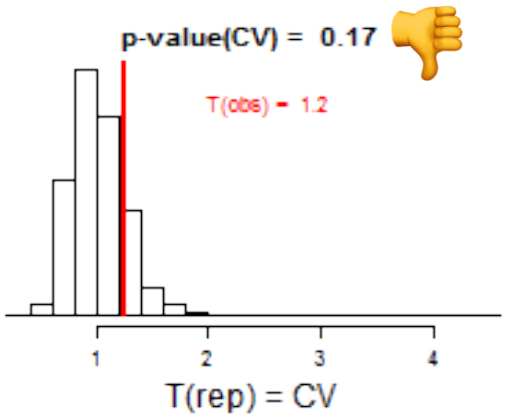
- Hypothetical data on number of failures for **a specific task type, specific set of PSFs**
  - 20 tasks (N_{task}), 10 repetitions (N_{rep}) of task by the same crew

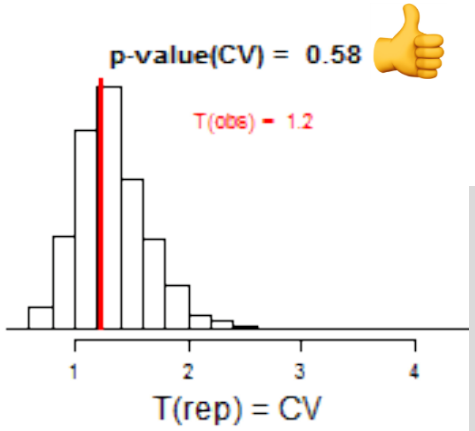
of failures on 10 repetitions
3
1
3
1
0
1
1
3
0
1
0
0
0
2
0
0
0
0
2
3





POSTERIOR PREDICTIVE CHECK



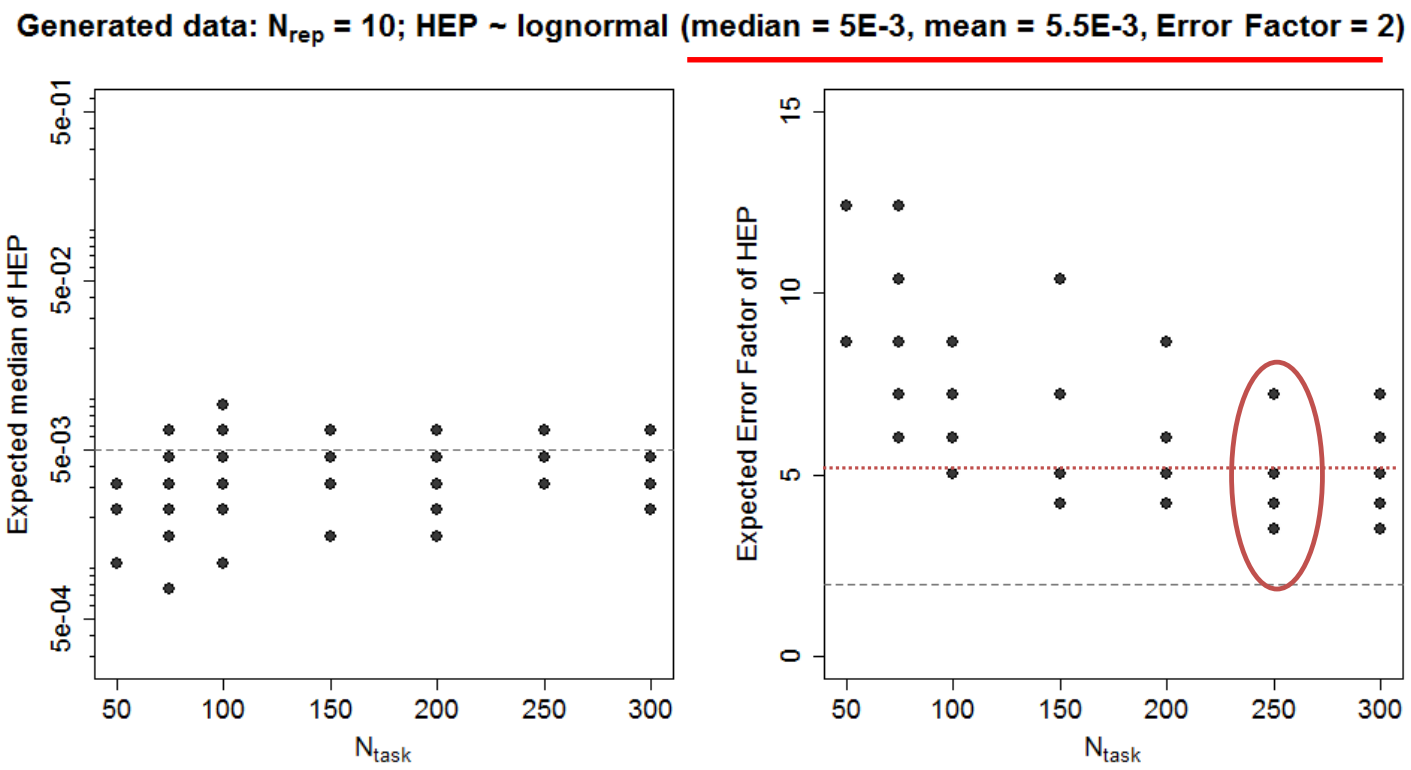


Overconfidence in the results if variability is not considered

Generated data: N_{task} = 20; N_{rep} = 10; HEP ~ lognormal (median = 0.05, mean = 0.08, Error Factor = 5)

Data requirements - How many tasks we need to simulate to inform on variability? case: median 5E-3

- Hypothetical data: 10 repetitions of same task by same crew are available (N_{rep}=10)



- As the number of simulated tasks increases, expected results get closer to the real values

More than 200 tasks are needed to know HEP with Error Factor < 5

- In this model the HEP is crew-specific: cannot aggregate data from different crews

Can we define "crew types"?

Three approaches compared

Generated data: median = 5E-2, EF = 2, N_t = 200

- Beta-Binomial: aggregates the 200 data points to inform on HEP value

# of failures	# of trials
11	200

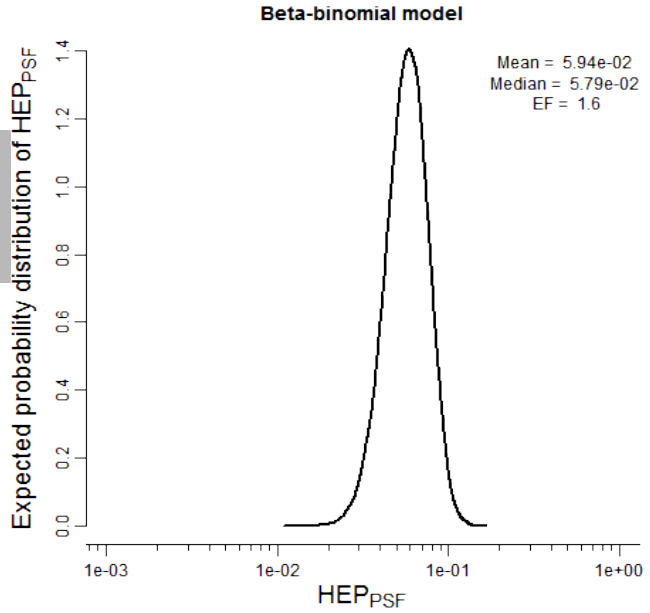
- Continuous variability model: each crew performance is the result of a single realization of a different HEP value

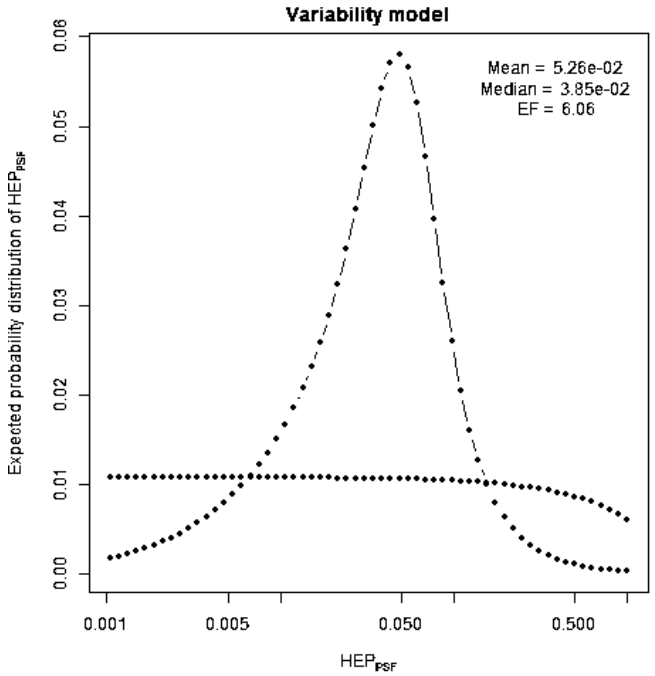
Data point	# of failures	# of trials
Crew # 1	0	1
..		
…		
Crew # …	1	1
Crew # Nt	0	1
TOTAL	11	200

- Discrete crew type model: aggregates data points pertaining to the same crew type

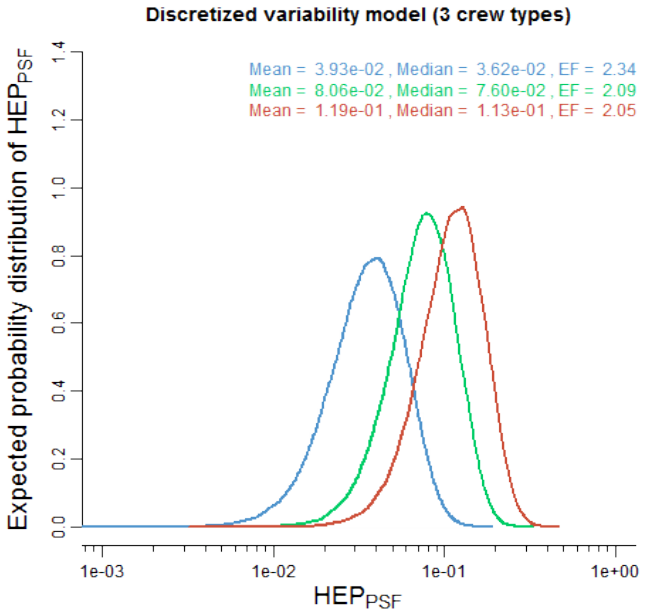
Data point	# of failures	# of trials
Crew type 1	3	100
Crew type 2	4	60
Crew type 3	4	40
TOTAL	11	200

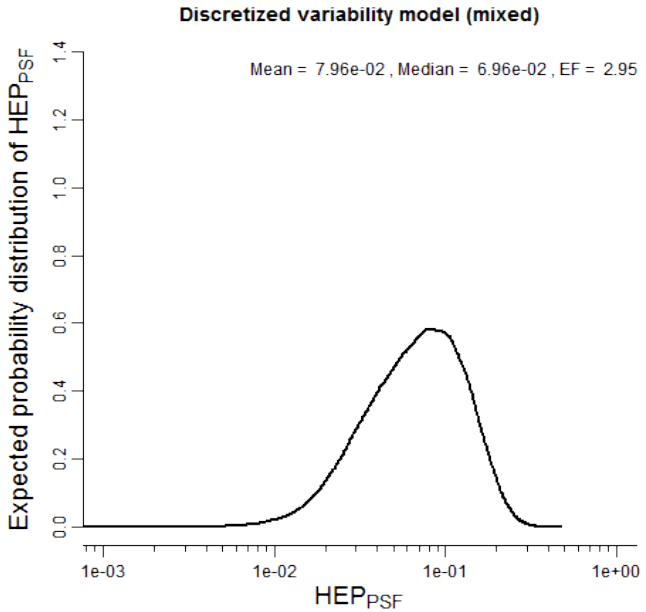
Generated data: median = 5E-2, EF = 2, N_t = 200





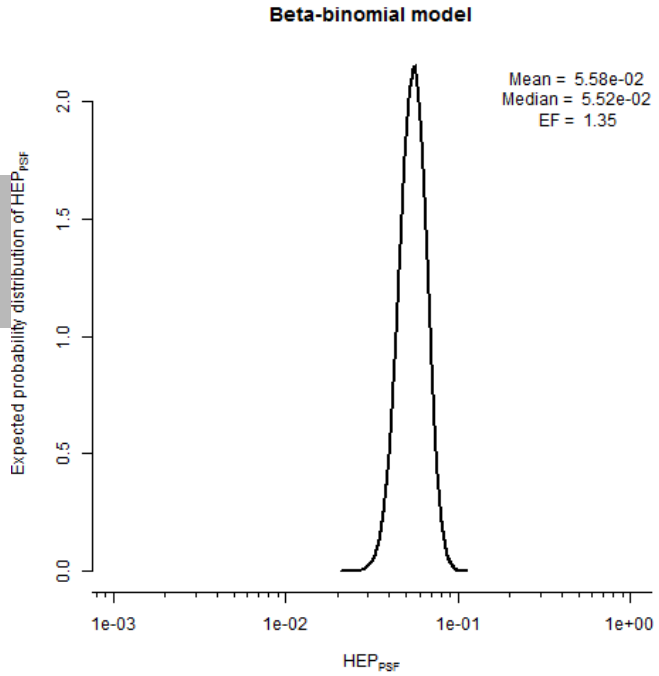
Aggregated data	# of UNSAT	# of TOEs
Crew type: 1 (blue)	3	100
Crew type: 2 (green)	4	60
Crew type: 3 (red)	4	40
TOTAL (black)	11	200

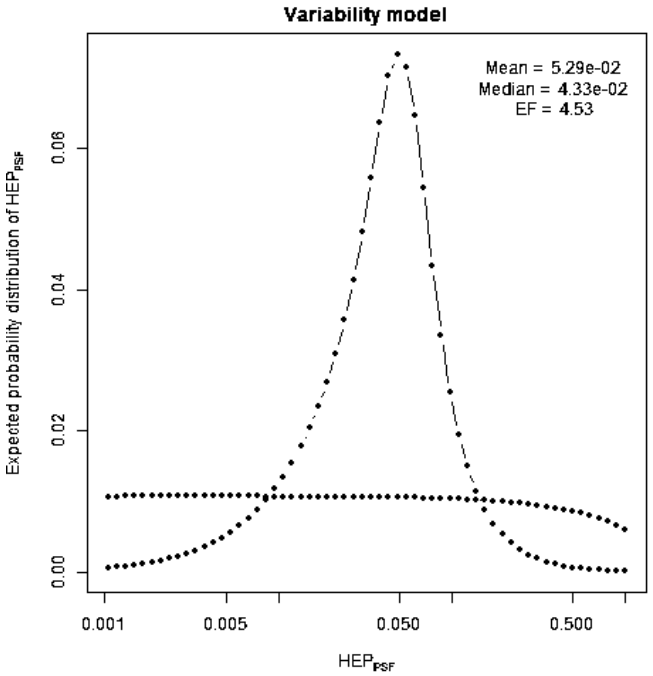




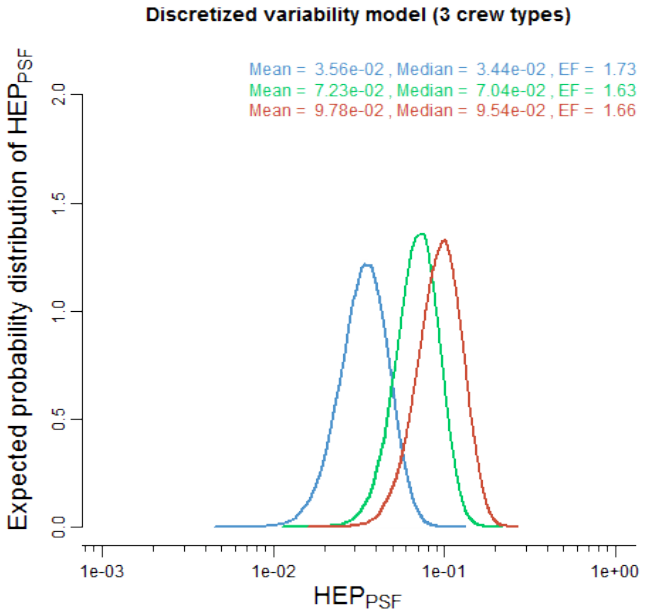
Generated data: median = 5E-2, EF = 2, N_t = 500

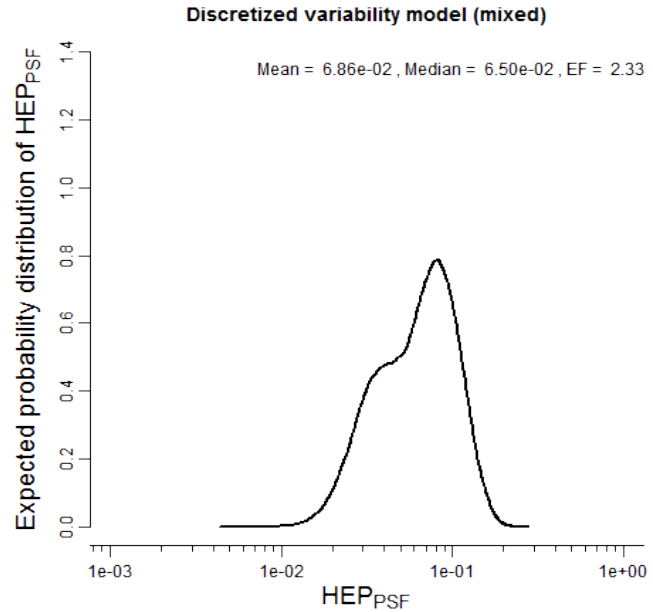
(seed: 222)





Aggregated data	# of UNSAT	# of TOEs
Crew type: 1 (blue)	8	250
Crew type: 2 (green)	10	150
Crew type: 3 (red)	9	100
TOTAL (black)	27	500





How to define crew types?

- Currently investigating literature on teamwork competences

- Can SACADA error causes be used to inform crew types? Eg.

Team skill	**Behavioural markers** O'Connor et al. (2008)	**SACADA error causes (Chang et al., 2014)**
Building situation awareness	Develop understanding	
	Anticipation	Lack of questioning attitude (Table B9)
	Maintain overview	Oversight failure: over focused (Table B8)
	Performance monitoring	Oversight failure: misplaced trust (Table B8)
Team focused decision making	Analytical decision making	Leadership failure: disrespect of others(Table B8)
	Procedure following	
	Intuitive decision making	Slow (Table B8)
	Initiative	Oversight failure: non-confrontational (Table B8)
Communication	Assertiveness	Too formal (Table B10)
	Information exchange	Unclear (Table B10)
Coordination	Adaptability	Rushing (Table B8)
	Supporting behaviour	Cohesion problem (Table B9)
	Team workload management	
Collaboration	Leadership	Leadership failure: overconfidence (Table B8)
	Co-operation	Experience mix (Table B9)
	Followership	Personality mix (Table B9)

Conclusions and outlook

- In typical HRA, uncertainty in the HEP estimates has been treated very simplistically
- A Bayesian model is developed, explicitly treating variability and uncertainty on the error probabilities
- The amount of tasks to be simulated to fully inform the variability model by data is probably impractical for probability values in the range of interest
- Way ahead:
  - Aggregation for crew operating styles
  - Increase collected evidence by using performance measures instead of “failure counts”
    - degree of success/failure as combination of performance in terms of safety variables, time, crew situation awareness
  - Expert judgment

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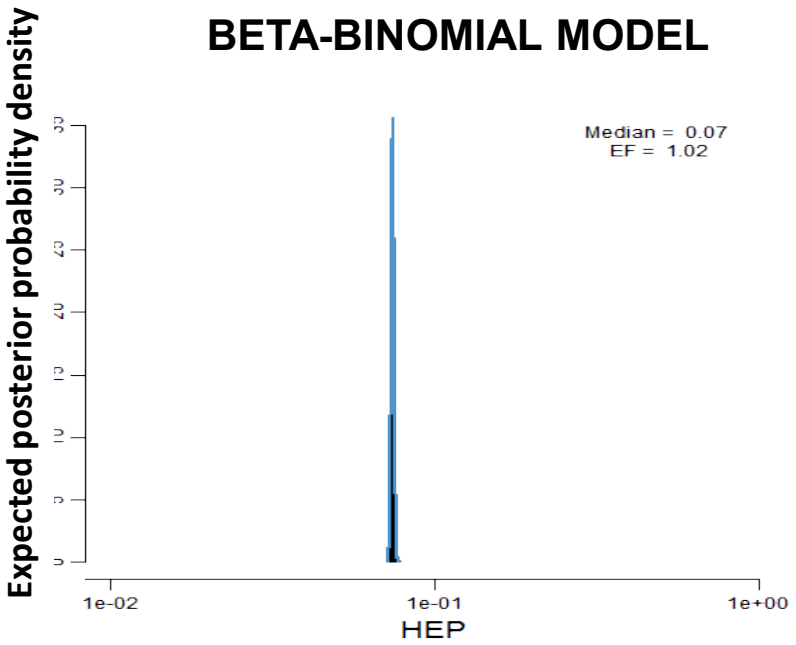
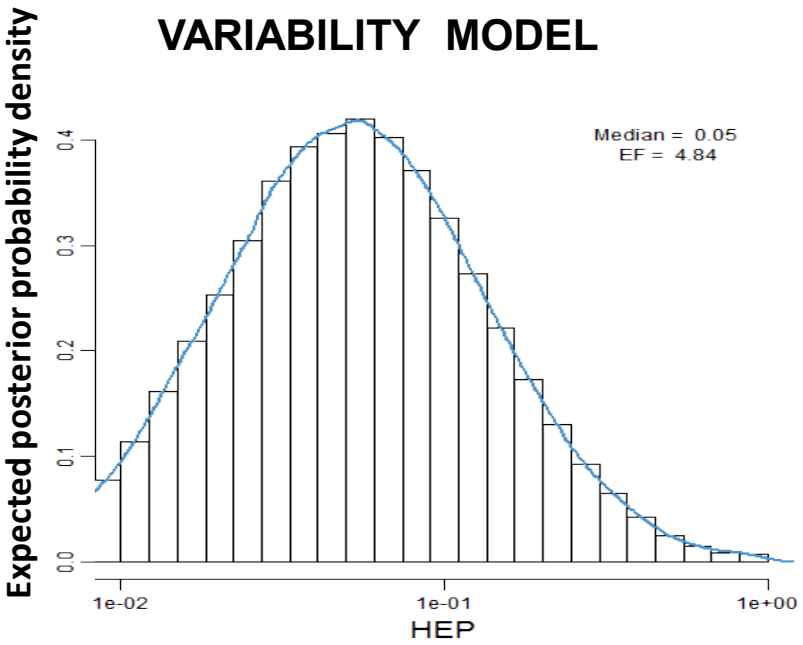
- Back up

With lots of data available …

- Hypothetical data on number of failures
  - 1000 tasks (N_{task}), 100 repetitions (N_{rep}) of task by the same crew

of failures on 1000 repetitions
209
53
204
36
60
47
30
235
80
12
135
10
23
100
37
13
11
57
95
…

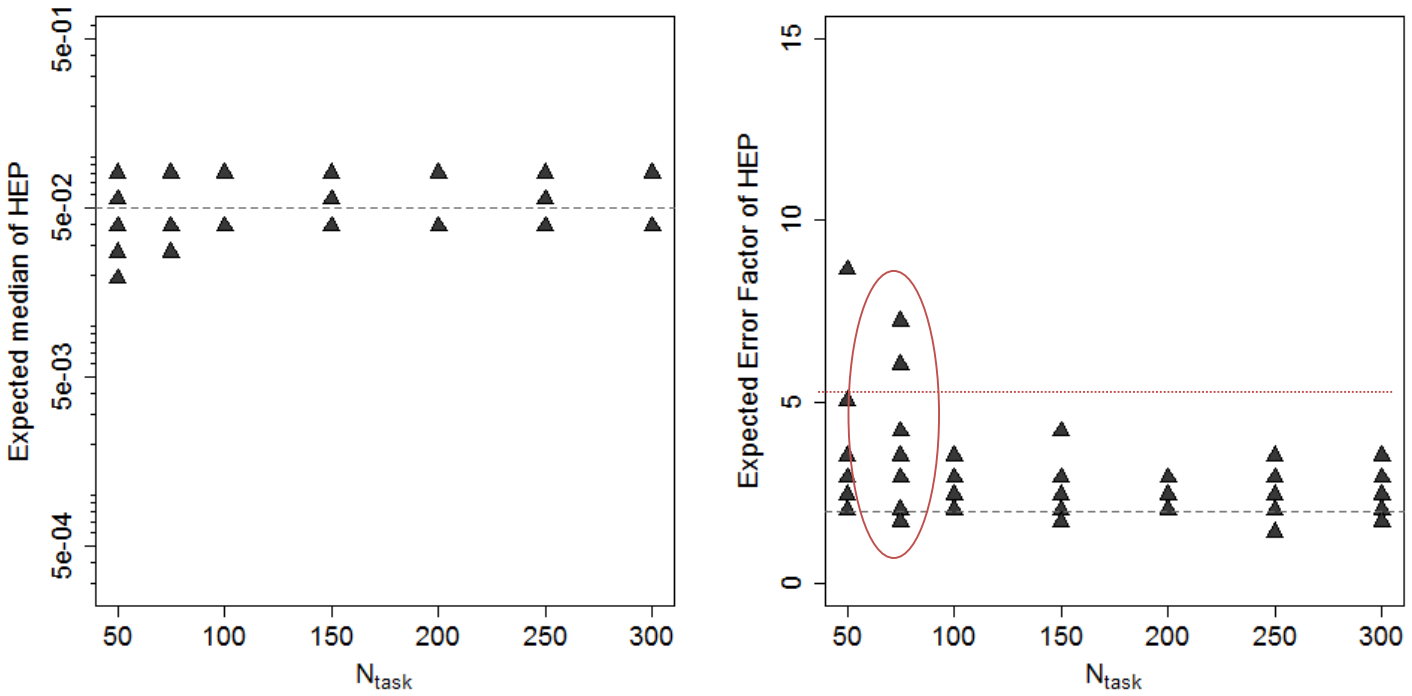




Data requirements - **How many tasks we need to simulate to inform on variability?** case: median 5E-2

- Hypothetical data: 10 repetitions of same task by same crew are available (N_{rep}=10)

Generated data: N_{rep} = 10; HEP ~ lognormal (median = 5E-2, mean = 5.5E-2, Error Factor = 2)

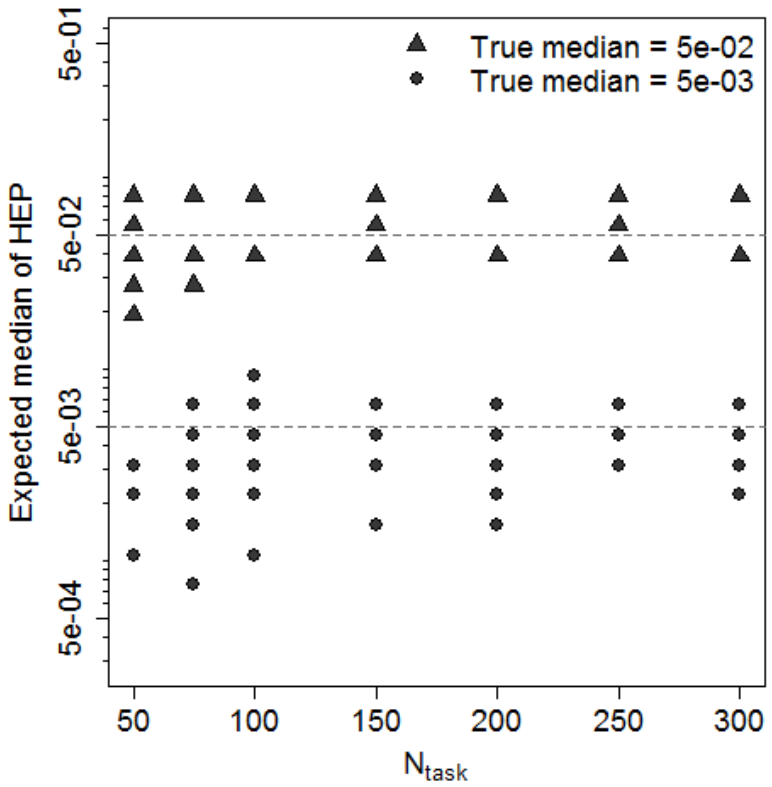


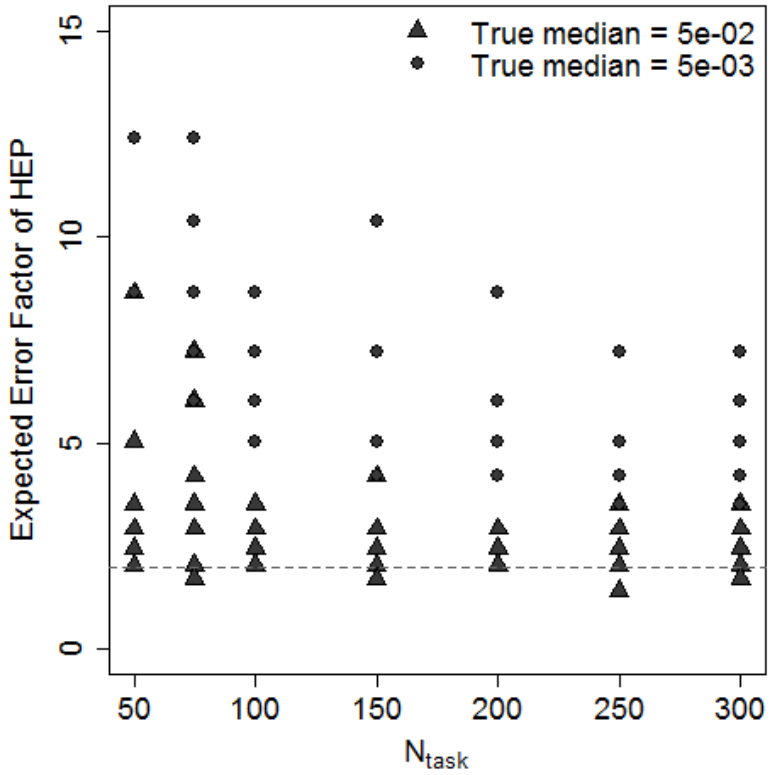
- As the number of simulated tasks increases, the expected results get closer to the real values
- **HEP with Error Factor < 5 already from 75 tasks**

Data requirements - **How many tasks we need to simulate to inform on variability?** cases compared

- Hypothetical data: 10 repetitions of same task by same crew are available (N_{rep}=10)

Generated data: N_{rep} = 10; HEP ~ lognormal (median = 5E-2 / 5E-3, mean = 5.5E-2 / 5.5E-2, Error Factor = 2)

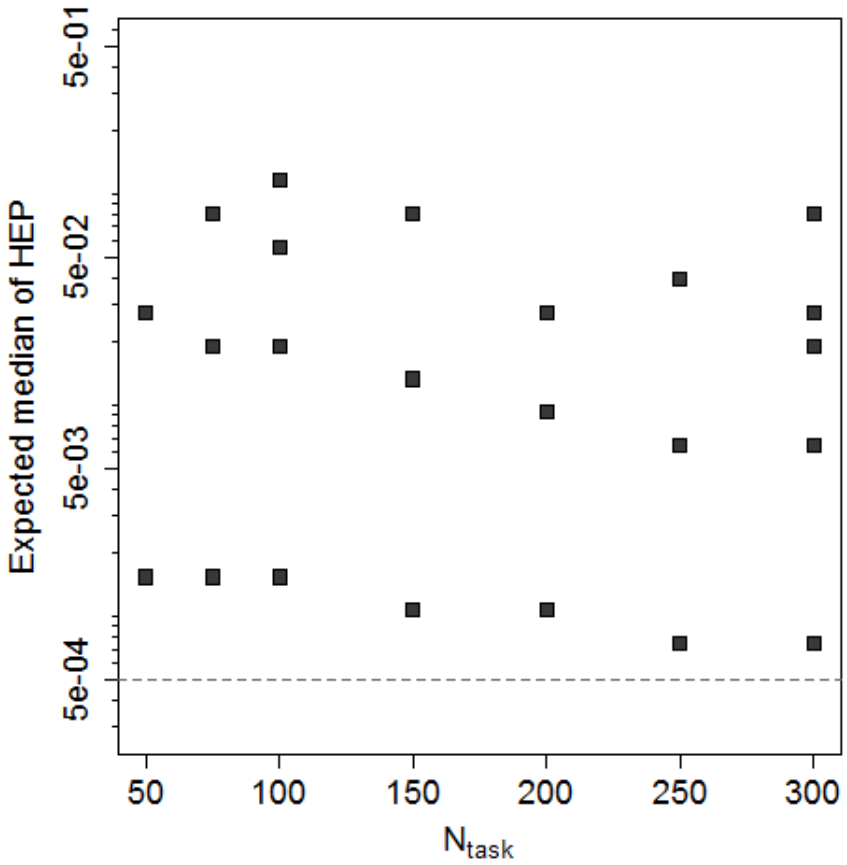


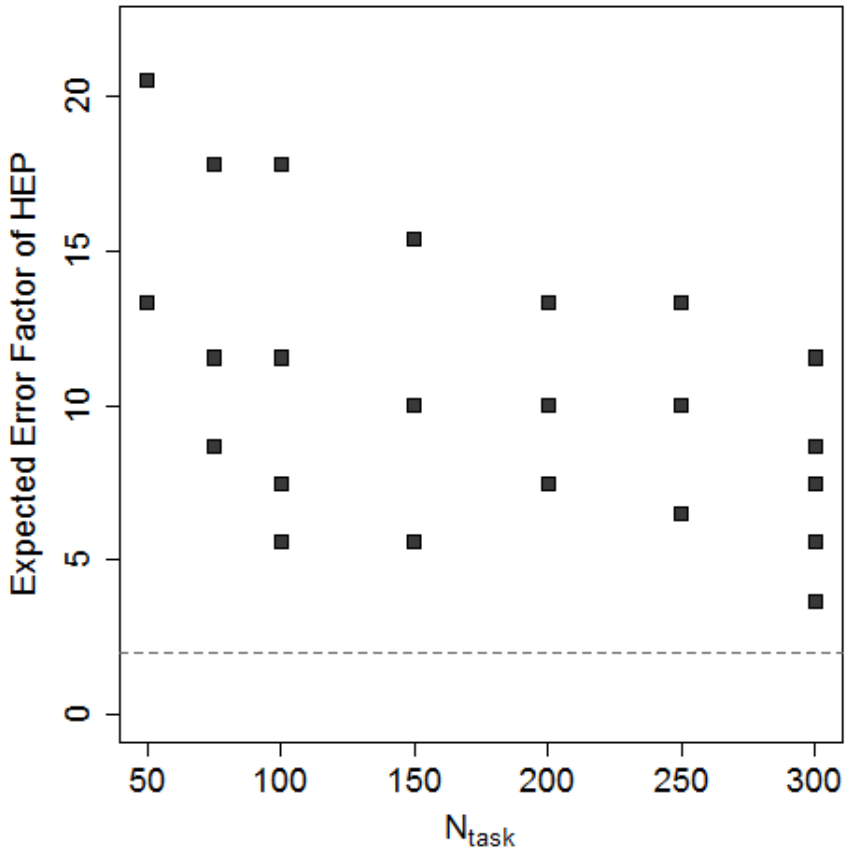


- As the number of simulated tasks increases, the expected results get closer to the real values

Data requirements - **How many tasks we need to simulate to inform on variability?** case: median 5E-4

Generated data: N_{rep} = 10; HEP ~ lognormal (median = 5E-4, mean = 5.5E-4, Error Factor = 2)

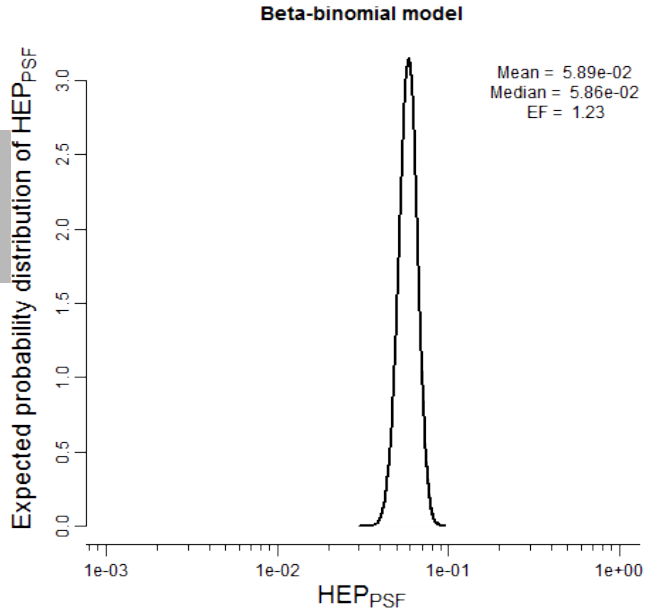


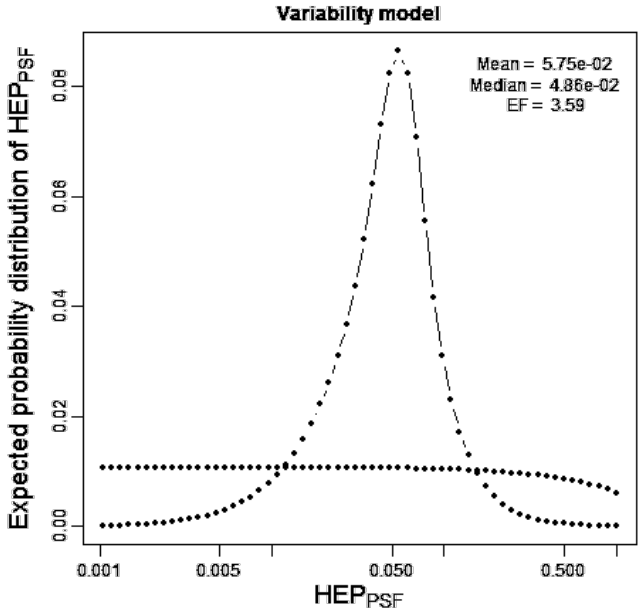


- As the number of simulated tasks increases, the expected results get closer to the real values

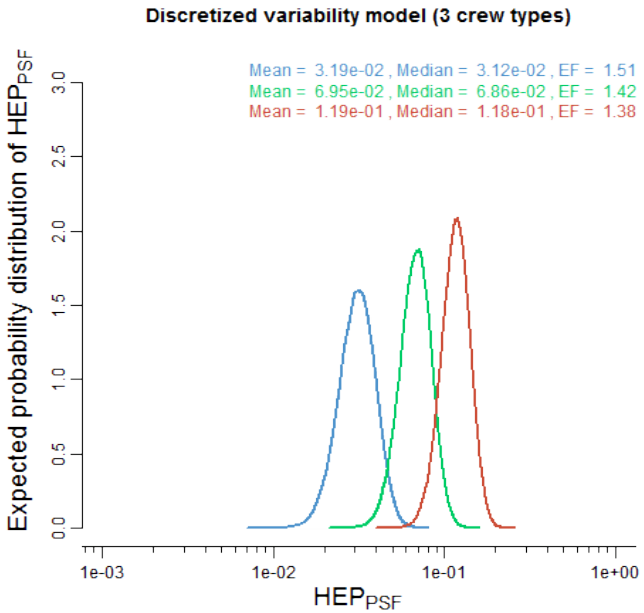
Generated data: median = 5E-2, EF = 2, N_t = 1000

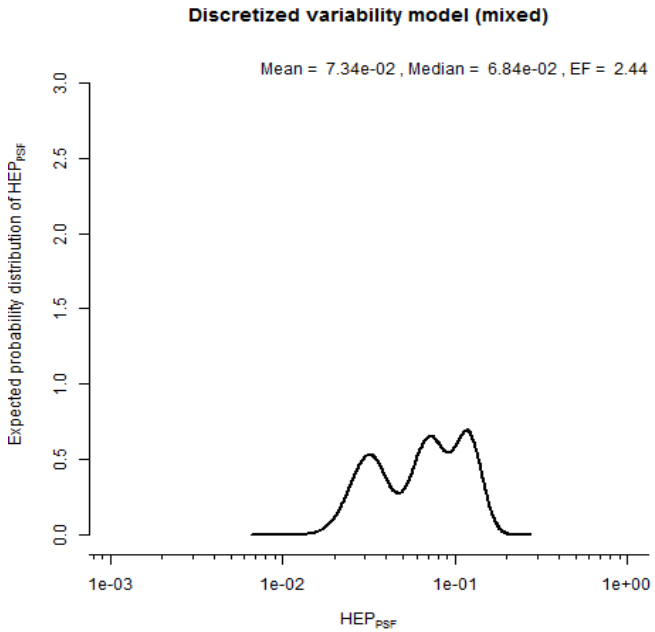
(seed: 222)





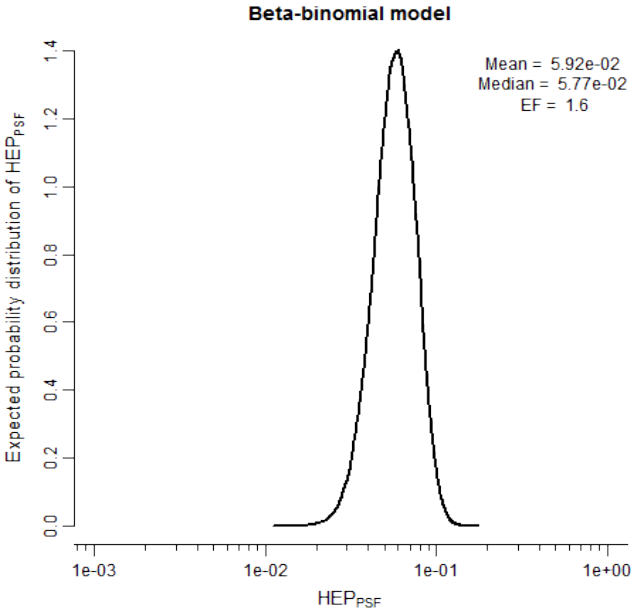
Aggregated data	# of UNSAT	# of TOEs
Crew type: 1 (blue)	15	500
Crew type: 2 (green)	20	300
Crew type: 3 (red)	23	200
TOTAL (black)	58	1000

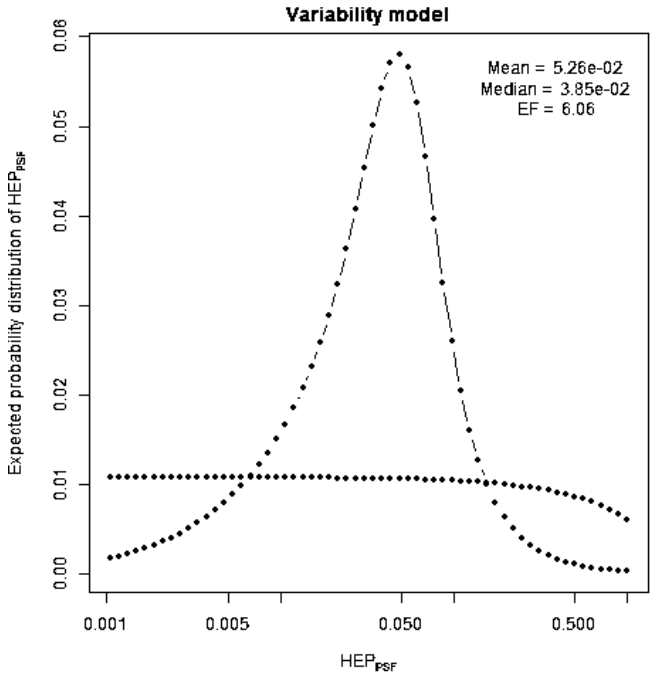




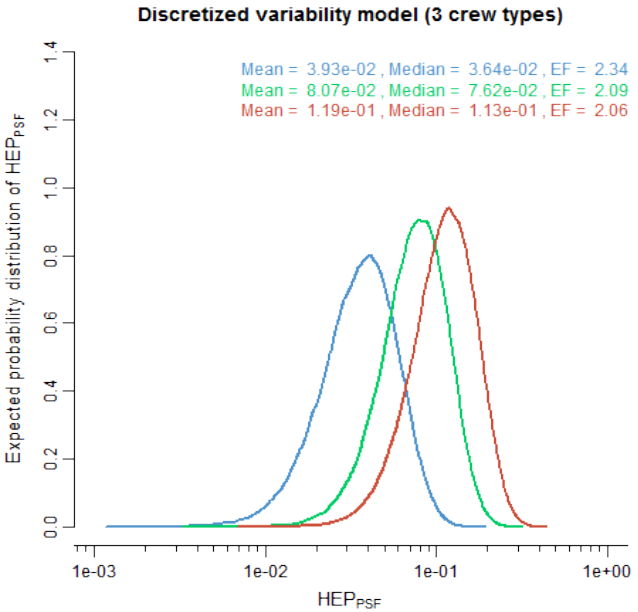
Generated data: median = 5E-2, EF = 3, N_t = 200

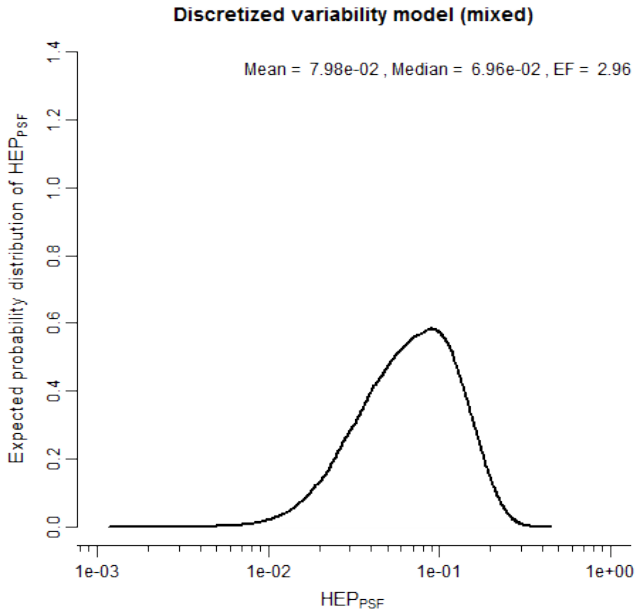
(seed: 222)





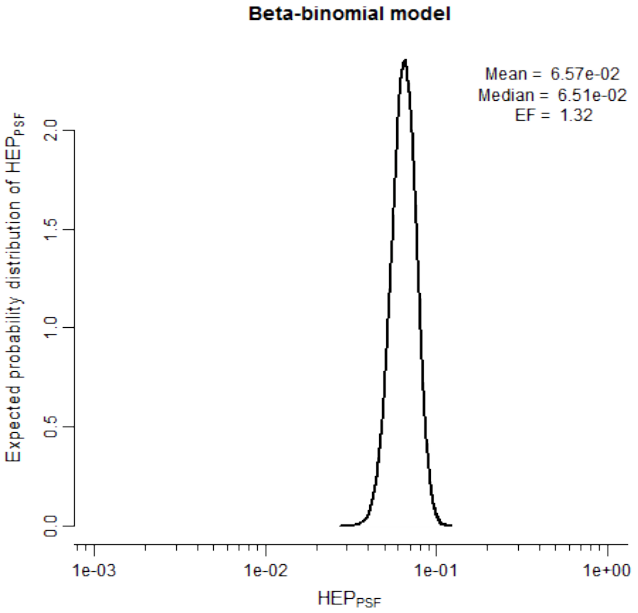
Aggregated data	# of UNSAT	# of TOEs
Crew type: 1 (blue)	3	100
Crew type: 2 (green)	4	60
Crew type: 3 (red)	4	40
TOTAL (black)	11	200

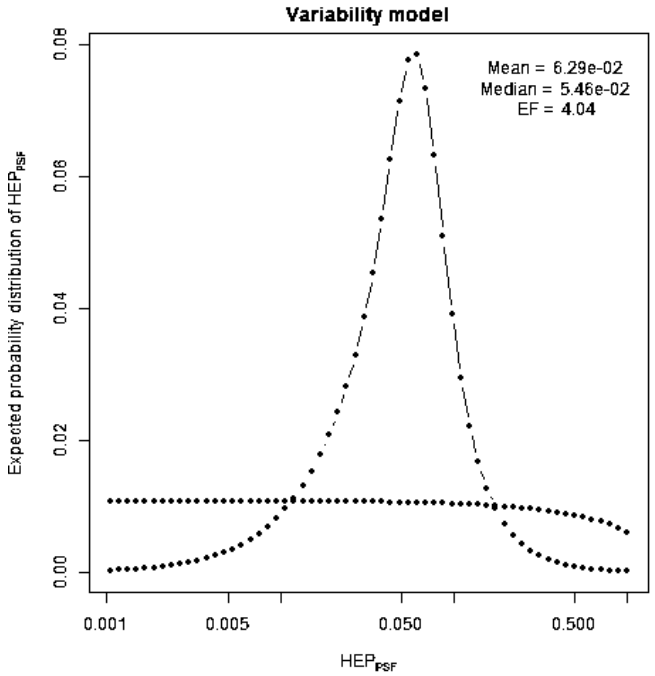




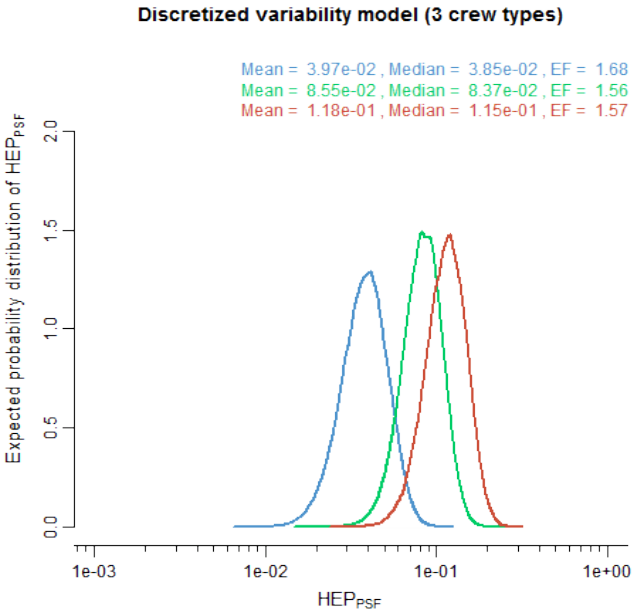
Generated data: median = 5E-2, EF = 3, N_t = 500

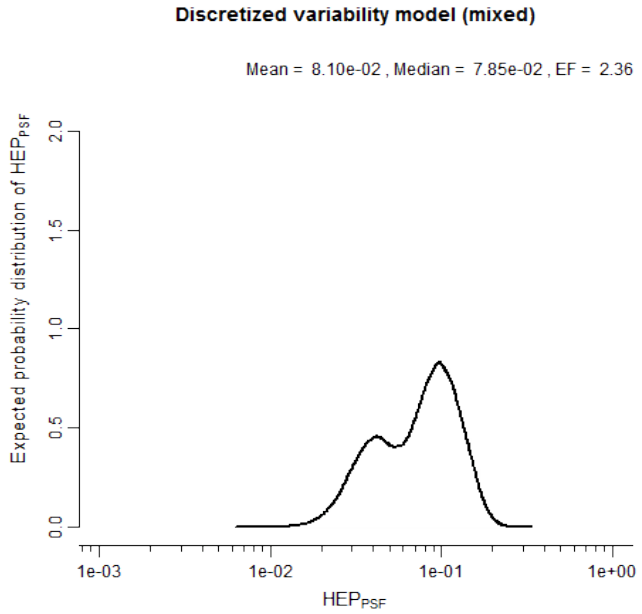
(seed: 222)





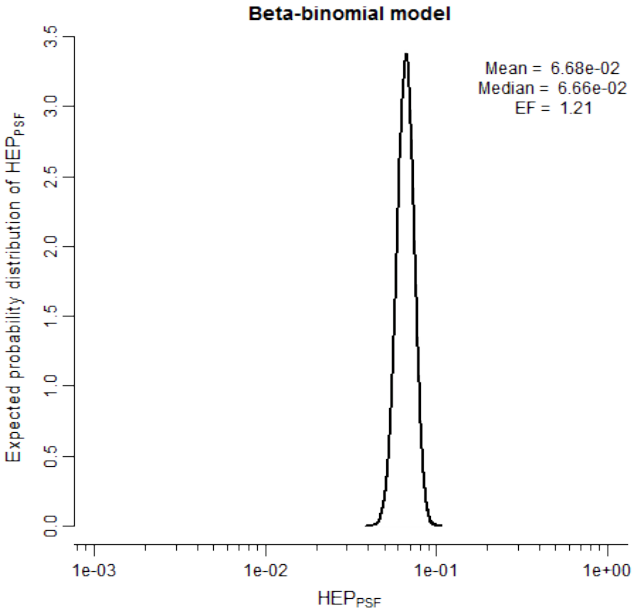
Aggregated data	# of UNSAT	# of TOEs
Crew type: 1 (blue)	9	250
Crew type: 2 (green)	12	150
Crew type: 3 (red)	11	100
TOTAL (black)	32	500

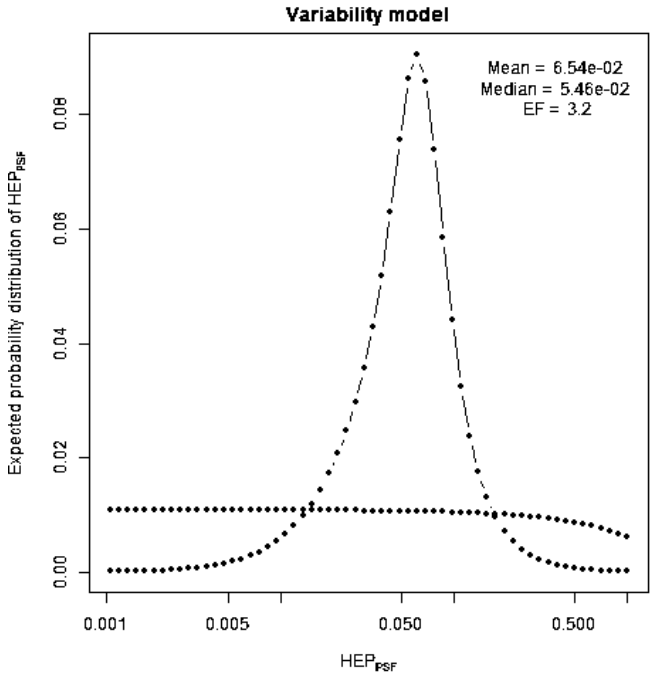




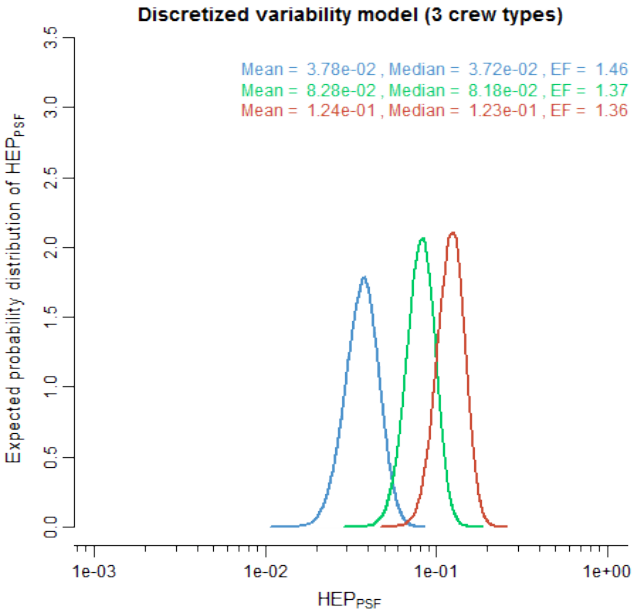
Generated data: median = 5E-2, EF = 3, N_t = 1000

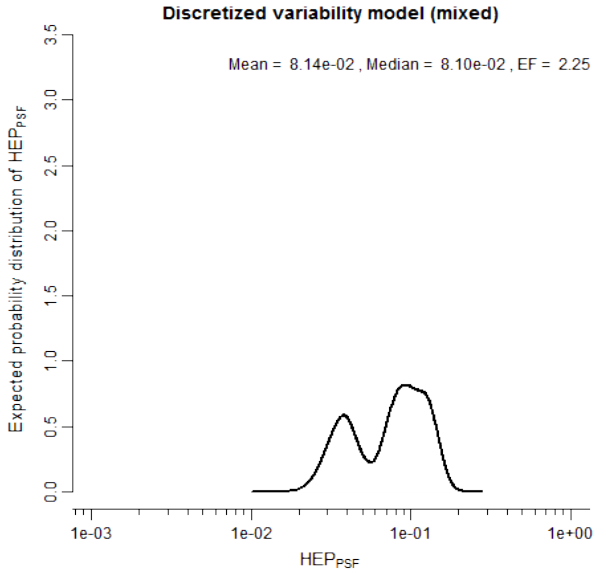
(seed: 222)





Aggregated data	# of UNSAT	# of TOEs
Crew type: 1 (blue)	18	500
Crew type: 2 (green)	24	300
Crew type: 3 (red)	24	200
TOTAL (black)	66	1000





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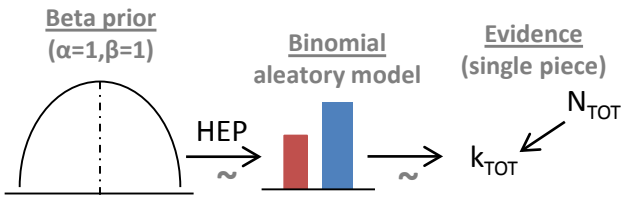
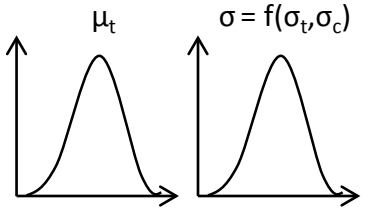
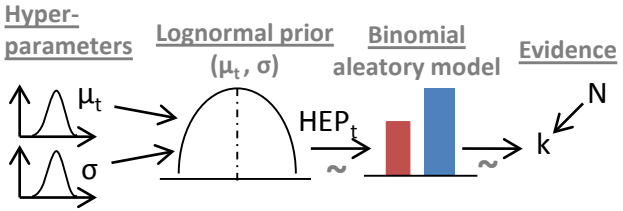
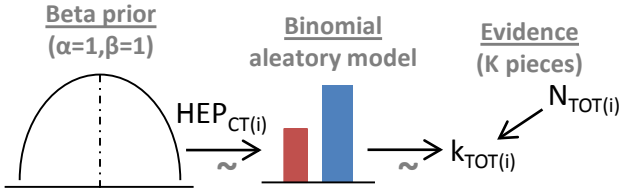
PSI

APPROACH	HYPOTHESES	VARIABLES (for each set F_{PSFs})	BAYESIAN INFERENCE MODEL
ØV Zero Variability	Unique HEP value associated to the same type of task, same set of PSFs Within-task, -PSF and crew variability represented by the probability itself	1 variable HEP	 $\pi(HEP_{PSF} \mid \alpha_{post},\beta_{post},E)$ = post. predictive $\alpha_{post} = \alpha_{prior} + k_{tot}$ $\beta_{post} = \beta_{prior} + N_{tot}$
FV Full Variability	HEP distribution associated to the same type of task, same set of PSFs A unique HEP value is associate to a specific task and scenario context, performed by a specific crew - Hierarchical model (two-stages), assuming lognormal var. functions	2 continuous variables  (after lognormal convolution)	 $\pi(HEP_{PSF} \mid \mu_t,\sigma,E)$ = post. predictive $\pi(\mu_t \mid E)$ = post. distribution of μ_t $\pi(\sigma \mid E)$ = post. distribution of σ
DCTV Discretized Crew-Type Variability	Unique HEP value associated to the same type of task, same set of PSFs, performed by the same type of crew Within-task, -PSF variability represented by the probability itself	K variables (K = crew types) 	 $\pi(HEP_{PSF} \mid \alpha_{post(i)},\beta_{post(i)},E_{(i)})$ = post. predictive $\alpha_{post(i)} = \alpha_{prior(i)} + k_{tot(i)}$ $B_{post(i)} = \beta_{prior(i)} + N_{tot(i)}$ [for the i-th crew type]