Uncertainty relating to human reliability

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Summary

- What does Statistical analysis do for you?
- What are the types of uncertainty in HRA and how do they arise?
  - Aleatoric uncertainty;
  - Epistemic uncertainty;
- What statistical techniques are best suited to coping with uncertainties in HRA?
  - The lack of data problem;
  - How do we propagate uncertainties?
  - How do we make decisions under uncertainty?
Statistical analysis

Data → Knowledge → Decision

Probability Modelling
Statistical inference
Point and Interval Estimation

Consequences and preferences
Decision making under uncertainty
Statistical analysis (Bayesian)

Data, Expert opinion \[\rightarrow\] Knowledge \[\rightarrow\] Decision

- Probability Modelling
- Statistical inference
- Point and Interval Estimation
- Elicitation

- Consequences and preferences
- Decision making under uncertainty
Statistical analysis

Data, Expert opinion

Probability Modelling
Statistical inference
Point and Interval Estimation
Elicitation

Knowledge

Consequences and preferences
Decision making under uncertainty

Decision

Usually the focus
Where are the uncertainties?

Data,

Expert opinion

Knowledge

Decision

Data model, censoring,...

Elicitation, biases, lack of background information

Posterior uncertainty, estimation error, confidence intervals

Consequences, preferences, type I and II errors
Epistemic and aleatoric uncertainty

• **Epistemic uncertainty:**
  - Uncertainties due to the fact that we don’t know something that we could in principle know;
  - In most cases, this is reduced by observing data.

• **Aleatoric:**
  - Uncertainties due to inherent variation in what happens;
  - Some philosophical objections to the concept;
  - Common example is measurement error.

• **Epistemic uncertainties can be reduced, aleatoric can only be quantified and managed.**
Examples of aleatoric uncertainty in HRA:

- Measurement error;
- Won’t say much more about these.
Epistemic uncertainties in HRA

Examples of epistemic uncertainty in HRA:

- The relationship between a particular human action and the probability of an accident;
- Human reaction to a situation;
- Bad reliability predictions because of ignored factors;
- Effect of missing data:
  - Under-reporting of bad decisions and risky events;
  - No baseline data (only reporting how often risky events occurred and not how often they didn’t).
Epistemic uncertainty and missing data

• The biggest cause of epistemic uncertainty in HRA is lack of data:
  • Difficult to implement proper controlled experiments e.g. as in drug trials;
  • Even if we could, they could be expensive/unethical to run;
    • Look to how drug trials handle the ethical side;
  • Often we are interested in rare events => need a lot of data to estimate incidence well;
  • A lot of reliance on observational studies e.g. incident reports;
Observational studies

- One difficulty is that they may only record data when an accident occurs:
  - This allows one to estimate quantities such as $P(\text{cause} | \text{accident})$;
- But to understand the importance of a particular effect, one wants $P(\text{accident} | \text{cause})$:
  - Bayes’ Law tells you:
    \[ P(\text{accident} | \text{cause}) = \frac{P(\text{accident}) \, P(\text{cause} | \text{accident})}{P(\text{cause})} \]
    where:
    \[ P(\text{cause}) = P(\text{cause} | \text{accident}) \, P(\text{accident}) + P(\text{cause} | \text{no accident}) \, (1 - P(\text{accident})) \]
  - What happened when no accident occurred is also needed.
Observational studies – example

In most sectors, it is now possible to collect data on day-to-day performance to deliver:

- \( P(\text{cause}) \)
- \( P(\text{cause} | \text{accident}) \)
- \( P(\text{accident}) \)
- \( P(\text{cause} | \text{no accident}) \)

Example:

1. Use of Flight data monitoring on deviations of flight performance from set parameters for normal operations.
2. Electronic journey logs for each flight reporting on threats and deviations.
3. Job cards for MX technicians.
What can you do about lack of data?

- Very little without extra assumptions!
- Generally, exploit dependencies to reduce uncertainties;
- Example from Bayesian learning literature: survival rates across 10 hospitals;

<table>
<thead>
<tr>
<th>Hospital</th>
<th>No. patients</th>
<th>No. survived</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>15</td>
<td>7</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>20</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>35</td>
<td>23</td>
</tr>
<tr>
<td>5</td>
<td>13</td>
<td>10</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>19</td>
<td>6</td>
</tr>
<tr>
<td>8</td>
<td>27</td>
<td>18</td>
</tr>
<tr>
<td>9</td>
<td>21</td>
<td>10</td>
</tr>
<tr>
<td>10</td>
<td>43</td>
<td>31</td>
</tr>
</tbody>
</table>

- Over all hospitals, $\frac{112}{196} = 57\%$ of patients survived;
- Do we expect inter-hospital variation? Yes!
- Do we really believe that the survival rate for hospital 2 is 100%?
- Or is it really 0% for hospital 6?
- What’s a reasonable way to “smooth” out the estimates?
Exchangeability (1)

- \( \theta_i = \text{Prob}(\text{survive in hospital } i) \);
- Exchangeability is a simple dependency, easy to justify (or not);
- Simply means that the order in which the hospitals are listed should not affect any inference you make from the data;
- Usually implemented by assuming \( \theta_i \)'s come from a common underlying population with some distribution \( p(\theta) \);
- Bayesian inference is the natural way to go as \( p(\theta) \) is a prior distribution;
Exchangeability (2)

- Inference results for exchangeable model compared to survival proportion;
- All estimates move towards the global survival percentage (57%);
- The amount that they move depends on how much data.

<table>
<thead>
<tr>
<th>Hospital</th>
<th>Survival Prob. $\theta_i$</th>
<th>Sample proportion $k_i/n_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Post. mean</td>
<td>95% prob. interval</td>
</tr>
<tr>
<td>1</td>
<td>0.51</td>
<td>(0.32,0.69)</td>
</tr>
<tr>
<td>2</td>
<td>0.61</td>
<td>(0.35,0.88)</td>
</tr>
<tr>
<td>3</td>
<td>0.37</td>
<td>(0.19,0.55)</td>
</tr>
<tr>
<td>4</td>
<td>0.63</td>
<td>(0.48,0.76)</td>
</tr>
<tr>
<td>5</td>
<td>0.66</td>
<td>(0.47,0.85)</td>
</tr>
<tr>
<td>6</td>
<td>0.51</td>
<td>(0.21,0.78)</td>
</tr>
<tr>
<td>7</td>
<td>0.41</td>
<td>(0.23,0.59)</td>
</tr>
<tr>
<td>8</td>
<td>0.63</td>
<td>(0.48,0.78)</td>
</tr>
<tr>
<td>9</td>
<td>0.51</td>
<td>(0.34,0.68)</td>
</tr>
<tr>
<td>10</td>
<td>0.68</td>
<td>(0.54,0.80)</td>
</tr>
</tbody>
</table>
Exchangeability and HRA

- Using data from one industry to infer reliability in another;
- Using data from nuclear industry to infer HR in other industries?
- Looking at the same risk across several ‘similar’ situations e.g. across different plants, different sites, etc.;
- Generally not applicable for time series data.
Expert Opinion (1)

- Quantifying uncertainties by expert opinion;
- Example: $\theta$ is a quantity that is known to be positive;
  - An expert’s best guess for the value of $\theta$ is 3, but thinks it might lie between 1 and 6;

![Graph showing a Gamma distribution with mean 3 and standard deviation 1.25. The interval (1,6) is marked as corresponding to mean ± 2 standard deviations, indicating that 96% of the distribution lies within this range.](image)
Expert Opinion (2)

- Bayes’ law used to update this distribution if data concerning $\theta$ is observed;

- Issues:
  - Combining different experts’ opinions;
  - Eliciting more complicated quantities:
    - Multivariate, correlations;
  - Sensitivity analysis.

- Elicitation works best when $\theta$ can be mapped from something observable
Design of Experiments

- A reminder that, if you are lucky enough to have a controlled experiment, there is a huge literature on the most efficient way to design it!

- Sample size determination, randomisation, factorial designs, etc.

- However crucial to the right Design of Experiment in HRA is also the issue of the “right representation of reality” (Dougherty 1990). The following aspects are often lacking:
  1. An appropriate representation of relevant error mechanisms as well as contextual and organizational conditions;
  2. Adequate dataset for the quantification of the error mechanisms as well as for the contextual and organizational conditions. (Straeter 2004)
Uncertainty quantification and propagation – common issues

1. Lacking of an adequate basis to validate these models against empirical data Mohaghegh and Mosleh (2009) “the absence of a comprehensive theory, or at least a set of principles and modeling guidelines rooted in theory and empirical studies”

2. Many of the models demonstrate very limited sensitivity of event probability to variation of single or multiple HOFs (or PSFs) (Trucco & Leva 2010),

3. Sometimes increasing model complexity can impede to justify modeling solutions, assure consistency and replicability, and eventually to return sound or realistic figures…”based on observations”..leading to “An often obfuscating numerology”(Dougherty 1990).. Due to weak measures of hardly measureable factors
Uncertainty quantification and propagation – belief networks

- Modelling the (uncertain) causal relationships between variables;
- Increasingly used in reliability assessments;
- $A \rightarrow B$ signifies that $A$ “causes” $B$;
- Probability of variable is conditional on value its parent variables;

Network for collision scenarios for a ship under power
Uncertainty quantification and propagation – belief networks

• Simplifies elicitation of risk when data not available;
  • Only need to specify probabilities of a node given parents.

• Fault trees can be mapped to a belief network:
  • Allows a fault tree analysis to incorporate uncertainty;
  • No more need to have independent events;
    • Common cause failures are easy to model;

• Explicit modelling of interactions between variables;
  • Time dependence can be modelled;

• Updating of probabilities in the tree via Bayes Law:
  • Coherent updating in light of data;
  • Scalable algorithms permit this even for large networks.
The Scenario: operator error to recover from collision course

\[ T_{dipe} = \frac{S_D}{V_r} \]

**LEGEND:**
- \( TA = (SD – SE) Vr \)
- If \( TDIPE > TA \) Then Collision Occurs
- \( TDIPE = \) Time for Detect, Interpret Planning and Execute the evasive maneuver
- \( SE = \) Minimum distance for performing the evasive maneuver.
- \( SD = \) Distance from the own ship at which the other ship starts to be detectable (by means of visual look out or radar/AIS)
- \( TA = \) time available to react
- \( V_r = \) relative speed
- \( Z = \) view zones
Task break down in THERP
Task break down in THERP

Issues:

- The Human Error Probabilities (HEP) are rather “insensible” to the context, that can only appear through the use of multiplication factors (PSF), slightly arbitrary. Thus No organizational factor actually explicitly appear in the model.

- The lack of data in the field does not enable the use of a data driven model for establishing links among those factors and the human actions, and the links among themselves.

Can we use data from nuclear industry??
A possible BBN related to detection
Modeling the detection phase

- The mean time between two successive look visual scan is affected specifically also by the node that take into account the Bridge Field of Vision “Bridge FOV”.

- The probability that the detection either by looking outside or by checking the radar/AIS is given according to an exponential distribution.

\[ P(t) = \int_0^t \lambda e^{-\lambda x} \, dx \]  
\( (1) \)

- Equation (1) represents the distribution of the probability of detection from 0 to the time t. the parameter \( \lambda \) is the looking frequency, which is to say the inverse of the mean interval of time between two successive scans.

Given the time available for visual or radar detection from the nodes of the scenario object, the total time available after detection is evaluated as maximum value between the two nodes "Ta R/A - Td R/A" and "Ta v - Td v".
Model related to planning
The control mode in planning

• Use of concept introduced by Hollnagel (1998) “Control Mode” to summarize the impact of:
  • time pressure,
  • competence of the operator and
  • the support for planning provided by the bridge layout.

• The node presents three possible states:
  • **Scrambled control**: the selection of the next action is unpredictable. (lowest level of control).
  • **Opportunistic control**: the selection of the next action is based on the current context without complete account of all factors.
  • **Tactical control**: performance is based on some form of planning.
Modelling the planning phase

The probability that the OOW either takes no decision or takes the wrong decision, assuming we know the time available for taking the decision is a conditional probability assigned according to a logit distribution.

\[
HEP(t) = P[HE(t) = 1 \mid t] = 1 - \frac{e^{\frac{(t-\mu)}{\sigma}}}{1 + e^{\frac{(t-\mu)}{\sigma}}}
\]

- the mean \((\mu)\) and the standard deviation \((\sigma)\) of the logit are calibrated using two pair of points \((T, HEP)\),
- \(T\) is a given interval of time available to perform a decision and
- \(HEP\) is the Human Error Probability of failing the planning.
- These two pairs are dependent on the given “Control Mode” state and the “Plan Complexity” state. First release of the model based on expert judgment.

- The pairs of value for the calibration can be in the future substitute by two possible couple coming from observational data (simulator training experiments).
From knowledge to decision

- Following the Bayesian path, there is a coherent theory of making optimal decisions:
  - Map preferences to utilities;
  - Take decision that maximises expected utility;
    - Why expected value? The “Dutch Book”!
  - Allows sequential decision making;
    - Full sequential decision making (usually impractical to implement);
    - Markov decision process.
- BBN + Decision Theory $\Rightarrow$ Influence Diagram
Influence diagrams
Influence diagram for pandemic intervention
Example: software testing

Utility of testing to time $T$ (negative cost):

$$U\{T, N(T), \overline{N}(T)\} = A - C N(T) - D \overline{N}(T) - F(T).$$

A probability model for $N(T)$ (we used a non-homogeneous Poisson process with mean function $a \cdot (1 - \exp(-bT))$);

Elicit expert opinion to get priors on $a$ and $b$;
Software testing (2)

Single stage testing

Sequential testing

Two stage testing
Software testing (3)

Markov decision process:
- Do single stage test;
- Update uncertainty on $a$ and $b$ with data from testing;
- Repeat until optimal test time is 0

Expected utility for single stage (based on prior only)
Concluding remarks

- “You may be uncertain, but you can be certain about your uncertainties”;

- A big toolbox of statistical/decision theory techniques can be applied to improve HRA;

- Bayesian attractive because of lack of data issue and the capacity to explicitly represent modeling assumptions;

- Gap between uncertainty quantification methods and physics/engineering/psychology.
Thank You
Example
Performance shaping factors: mapping factors to human error probability $P_{HE}$

1st generation methods:
- THERP (*Technique for Human Error Rate Prediction*)
- SPAR-H (*Standardized Plant Analysis Human Reliability*)
- TESEO (*Tecnica Empirica per la Stima dell’HE*)
- HEART (*Human Error Assessment and Reduction Technique*)

2nd generation methods:
- CREAM (Cognitive Reliability and Error Analysis Method)
- HCR (Human Cognitive Reliability)
- ATHEANA (A Technique for Human Event ANAlysis)

Performance Shaping Factors PSFs

stress, ergonomy, education, training, organisation of tasks, co-operation, time availability...
Performance shaping factors: mapping factors to human error probability

**Aim:** evaluation of the **uncertainty of** $P_{HE}$ due to the assignment of the values quantifying the PSFs.

**Method:** **Computing and testing a** $P_{HE}$ **quantification model** in relation to selected HR methods:

Exploiting this model in a MC to simulate $P_{HE}$ in very **different** boundary conditions relating to PSFs.
Computing & testing a $P_{HE}$ quantification model

**Hypothesis:** selecting HR methods more similar in PSFs assignment and returning the estimates of $P_{HE}$ with each method.

**Method:** in order to minimize the amount of input ascribed to the risk analyst, the model contains some correlating assumptions for the assignment of different PSFs.
Computing & testing a $P_{\text{HE}}$ quantification model

- Emergency condition
- Potential emergency condition
- Normal operative condition
Impact of the uncertainty related to HE $[P_{HE}]$

**Hypothesis:** the random assignment of PSFs follows a discrete uniform PDF.

**Method:** A Monte Carlo method has been implemented with 100 000 iterations.

At each iteration:

1. MC randomly assigns each level to PSFs, so the related corrective value for $P_{HE}$;

2. MC evaluates $P_{HE}$ for each HR method.
Impact of the uncertainty related to HE $[P_{HE}]$

\[ P_{HESPARRH} = \frac{P_{HE_{nom}} \cdot \prod_{k=1}^{n} PSF_k}{1 + P_{HE_{nom}} \cdot \prod_{k=1}^{n} (PSF_k - 1)} \]

\[ P_{HETESEO} = PSF_1 \cdot PSF_2 \cdot PSF_3 \cdot PSF_4 \]

\[ P_{HECREAM} = P_{HE_{nom}} \cdot \sum_{k=1}^{9} PSF_k \]

\[ P_{HEHCR} = \exp \left( -\left( \frac{\mu - \gamma}{\eta} \right)^\beta \right) \]

- $P_{HESPARRH} = 1.789E-01 \pm 3.072E-01$
- $P_{HETESEO} = 2.577E-01 \pm 2.798E-01$
- $P_{HECREAM} = 4.229E-02 \pm 5.824E-02$
- $P_{HEHCR} = 2.144E-01 \pm 2.689E-01$
Results from MC simulation: $E[\text{HEP}]$, $\sigma[\text{HEP}]$

\[ E[\text{HEP}] = \text{Sample Average} = \frac{\sum_{i=N}^{\text{iter}} \text{HEP}_i}{\text{iter}} \]

\[ \sigma[\text{HEP}] = \text{Variance} = \sum_{i=N}^{\text{iter}} \frac{\text{HEP}_i}{i} - \frac{\sum_{i=N}^{\text{iter}} \text{HEP}_i}{\text{iter}} \]
Results from MC simulation: PDF(HEP) and F(HEP)
Impact of the uncertainty related to HE \([P_{HE}]\)

- \(f_{\text{extended dispersion}} = 6.45 \times 10^{-5} \pm 3.165 \times 10^{-4} \) [event/year]
- \(f_{\text{dispersion}} = 1.494 \times 10^{-3} \pm 4.062 \times 10^{-3} \) [year]
  \(f_i > 0\)
- \(f_{\text{extended fire}} = 6.59 \times 10^{-6} \pm 3.083 \times 10^{-5} \) [event/year]
- \(f_{\text{fire}} = 1.514 \times 10^{-4} \pm 4.132 \times 10^{-4} \) [year]
Example conclusion

The assignment of PSFs creates an important uncertainty on the failure probability of the operator.

- Effective deterrent used to encourage safety culture.
- Reason for continuously investing on initiatives to hold human error down.
- Being sure to have at disposal an active part for the plant safety, able to diagnose ad hoc.
Thank You
Fault tree and belief network
Uncertainty quantification and propagation – belief networks

- Specifying a probability for each base event + tree logic => probability for top event;
- Networks most useful when there is uncertainty in these probabilities!
- Specify uncertainty as a probability distribution;
- Distributions on probability for each base event + tree logic => distribution (uncertainty) on probability for top event
Belief network example – initial fault tree
Distributions on probabilities of base events before and after data