COSSAN Case Study

Using Credal network to estimate human error probabilities

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Summary and Key Finding

Key Findings

By using the OpenCossan toolbox for Credal network, it was possible to model the factors that triggers human errors. This model allowed to study the following aspects:

1. **Human error probability under specific organisational and technological factors.**
2. **Conditional probabilities even when no information is available for certain combination of factors - without needing to use expert judgement**.
3. **Representation of the information available and its uncertainty, showing results within lower and upper boundaries**

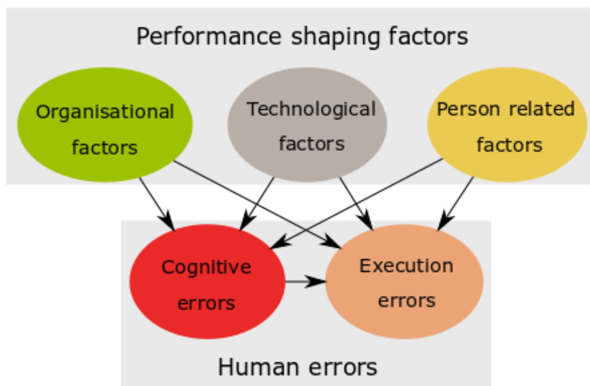


Figure 1: A simple model of human errors affected by performance shaping factors

1 Problem Description

1.1 The need to assess human error probability

This case study presents the following example: a team is designing a new chemical plant where an operator has to open an equipment door only after its internal pressure drops. This operating pressure is high enough to cause a fatality, so the operator has to wait to open the equipment door at the right moment by observing a pressure gauge (see Morais et al. [2018]).

After identifying the hazard, the team has to know if the risk level of this operation meets the risk criteria of their organisation (or the safety regulator). If not, they have to recommend additional safety barriers.

To assess the overall risk level of this operation, not only the equipment failure has to be accounted, but also the human error. That is because, for an operator to open the equipment door at the wrong moment, one of the two following errors have to happen before: the operator failing to observe the pressure gauge or the pressure gauge displaying a false measure.

The pressure gauge supplier has informed its failure rate. How does a team should assess the probability of an operator failing to observe the pressure gauge? This is usually called human error probability, and this Case Study presents a way of obtaining it even when some data are not available.

2 Analysis

To estimate the probability of an operator of failing to read a pressure gauge, the risk assessors decided to model the relation between factors (e.g. organisational) and human errors using Bayesian networks. The first objective is to obtain human error probabilities. The second objective is to show how the different factors involved can contribute to the human error.

The probabilistic tool to analyse this case study uses Bayesian network with credal sets, or simply 'Credal network'.The Bayesian network framework allows using data from different sources (e.g. expert interviews, safety inspections). The probabilistic information is put inside the so known Conditional Probability Tables and the network is generated with the Bayesian network toolbox of OpenCossan (see Patelli [2012]).

For this case study, the assessors have used a dataset obtained from major accident reports Moura et al. [2017].The dataset uses a taxonomy named CREAM (Hollnagel, 1998). In this taxonomy, the human error of 'failing to read a pressure gauge' is called 'observation missed', represented in the model of Figure 2 as the node in red.

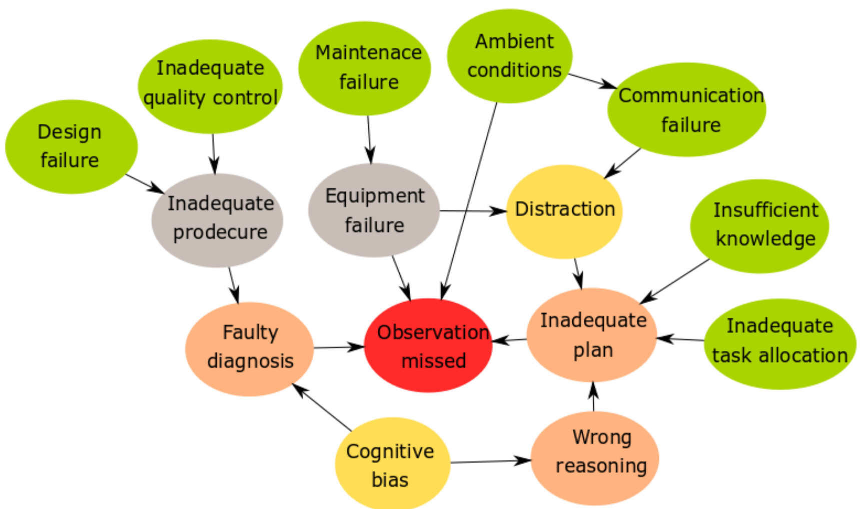


Figure 2: Model of organisational factors (in green), technological factors (in gray) and person related factors (in yellow), that lead to the human errors (in orange and red)

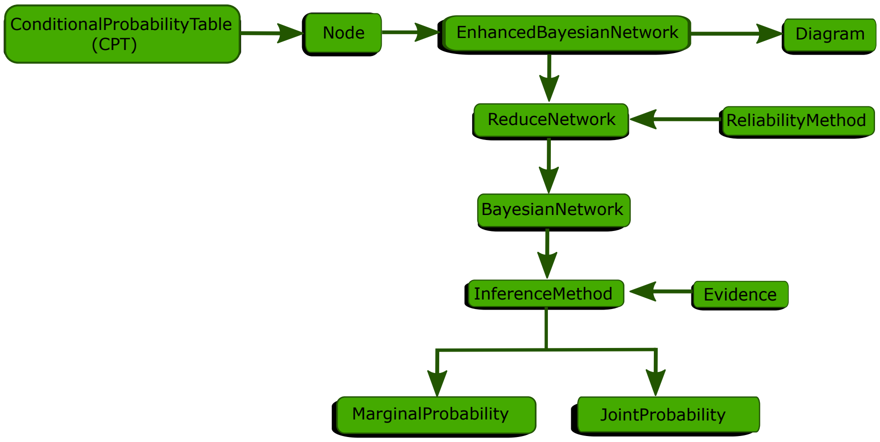
The problem is that the dataset chosen did not provide all the possible combinations needed to fulfill the conditional probability table. That means that some combinations do not sum to one. The Figure 3 shows a part of a conditional probability table from this dataset, where the states 'occurred' and 'not occurred' designate whether or not a human error or factor was observed on an accident report.

Equipment failure		State 'not occurred'				(...)
Ambient conditions		State 'not occurred'				(...)
Inadequate plan		State 'not occurred'		State 'occurred'		(...)
Faulty diagnosis		State 'not occurred'	State 'occurred'	State 'not occurred'	State 'occurred'	(...)
Observation missed	State 'not occurred'	0.4	0	0	0	(...)
	State 'occurred'	0.6	0	0	1	(...)

Figure 3: Conditional probability table for child node 'Observation missed', showing possible combinations that are not informed by the dataset

2.1 Implementation

The structure to built the Credal network model on OpenCossan is shown in Figure 2, and it is basically the same used to the Bayesian network toolbox. This toolbox allows to work with continuous distribution variables and with discrete variables. New information can be input (evidence) and obtain as output the Marginal and/or Joint probabilities of the queried variables.



A summary of the code implementation to this specific case study is shown below. For a better understanding on the sintax used on the code, please visit https://cossan.co.uk/wiki/index.php/BayesianNetwork

```
%% Human Error Model: Version 1
% addpath('C:\OpenCossan\branches\EBNtesting\COSSANXengine\src')

import bayesiannetwork.Node
import bayesiannetwork.EnhancedBayesianNetwork

% initialize variable n (number of nodes in the net)
n=0;

%%%%%%% Root nodes %%%%%%%%%%%%

% Node Maintenance Failure (state 1= not occurred; state 2= occurred)
n=n+1;
CPT_Maintenance = cell(1,2);
CPT_Maintenance{1,1} = 0.65;
CPT_Maintenance{1,2} = 0.35;
CXnodes{1,n}=Node('Sname','Maintenance','CPD',CPT_Maintenance,'Stype',...
'discrete','Nsize',2,'Lroot',true);

% ALL OTHER ROOT NODES WILL FOLLOW THE FORMAT FOR THE NODE 'MAINTENANCE    %
FAILURE'
```

This is the representation of this table:

	State 'not occurred'	State 'occurred'
Maintenance failure	0.65	0.35

```
%% %%%%%%%%%%%%%%%% Children nodes %%%%%%%%%%%%%%%%%%%%%%%%%%%

%% Children with one parent %%

% Node Equipment Failure
n=n+1;
CPT_EquipmentFailure = cell(2,2);
CPT_EquipmentFailure([1,2],1) ={0.5161, 0.3253 } ;
CPT_EquipmentFailure([1,2],2) ={0.4838, 0.6746 } ;
CXnodes{1,n}=Node('Sname','EquipmentFailure','CPD', ...
CPT_EquipmentFailure, 'Stype','discrete', ...
'Nsize',2,'CSparents',{'Maintenance'});

% ALL OTHER CHILD NODES WITH ONE PARENT WILL FOLLOW
THE FORMAT   % FOR THE NODE 'EQUIPMENT FAILURE'
```

This is the representation of the table below:

	Maintenance failure	
Equipment failure	State 'not occurred'	State 'occurred'
State 'not occurred'	0.5161	0.3253
State 'occurred'	0.4838	0.6746

```
%%% Children with two parents %%%

% Node Distraction
n=n+1;
CPT_Distraction = cell(2,2,2);
CPT_Distraction(1,1,[1,2])={0.9375, 0.0625};
CPT_Distraction(1,2,[1,2])={0.6363, 0.3636};
CPT_Distraction(2,1,[1,2])={0.9743, 0.02564};
CPT_Distraction(2,2,[1,2])={0.9285, 0.07142};
CXnodes{1,n}=Node('Sname','Distraction','CPD',CPT_Distraction,'Stype', ...
'discrete','Nsize',2,'CSparents',{'EquipmentFailure','Communication'});
```

This is the representation of the table below:

Equipment failure		State 'not occurred'		State 'occurred'	
Communication failure		State 'not occurred'	State 'occurred'	State 'not occurred'	State 'occurred'
Distraction	State 'not occurred'	0.9375	0.6363	0.9743	0.9285
	State 'occurred'	0.0625	0.3636	0.02564	0.07142

```
% ALL OTHER CHILD NODES WITH TWO PARENTS WILL FOLLOW THE FORMAT FOR THE NODE
'DISTRACTION'
```

In order to overcome the limitations of lack of data for some nodes, Credal Networks have been proposed to integrate Bayesian Networks with imprecise probabilities which, allow to fully represent the information available and its uncertainty (see Tolo et al. [2018]).

```
%% %%%%%%%%%%%%%%%% Credal Nodes %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% These nodes are the ones where data does not provide prior probabilities for
some of the combinations within some variables states. In practice, it returns a
sum of '0' for the probabilities - making it impossible to compute the
conditional probability table. The code below will compute all the possibilities
of prior probabilities, varying the states with missing data from 0 to 1. This
way, the user will have the uncertainty of those scenarios captured, as the
outputs will have lower and upper boundaries.
```

Equipment failure		*State 'not occurred'*				*(...)*
Ambient conditions		*State 'not occurred'*				*(...)*
Inadequate plan		*State 'not occurred'*		*State 'occurred'*		*(...)*
Faulty diagnosis		*State 'not occurred'*	*State 'occurred'*	*State 'not occurred'*	*State 'occurred'*	*(...)*
Observation missed	*State 'not occurred'*	*0.4*	*0*	*0*	*0*	*(...)*
	State 'occurred'	*0.6*	*0*	*0*	*1*	*(...)*

```
 % Inadequate Plan
n=n+1;
VSizes= [2,2,2,2,2]; %includes parents sizes (right order as in CSparents!!!)
plus number of states of the node under definition
CPT_InadequatePlan_lower =
common.utilities.importCPTfromGenie('C:\Users\cmorais\Desktop\InadequatePlanCPT.t
xt',VSizes);
CPT_InadequatePlan_upper =
common.utilities.switch2upperExtreme(CPT_InadequatePlan_lower);

CXnodes{1,n}=Node('Sname','InadequatePlan','CPD',{CPT_InadequatePlan_lower, ...
CPT_InadequatePlan_upper},'Stype','discrete','Nsize',2,'Lpbounds',true, ...
'CSparents',{'WrongReasoning','Distraction','TaskAllocation','Knowledge'});

% Observation Missed
n=n+1;
VSizes= [2,2,2,2,2]; %includes parents sizes (right order as in CSparents!!!)
plus number of states of the node under definition
CPT_ObservationMissed_lower =
common.utilities.importCPTfromGenie('C:\Users\cmorais\Desktop\ObservationMissedCP
T.txt',VSizes);
CPT_ObservationMissed_upper =
common.utilities.switch2upperExtreme(CPT_ObservationMissed_lower);

CXnodes{1,n}=Node('Sname','ObservationMissed','CPD',{CPT_ObservationMissed_lower,
CPT_ObservationMissed_upper},'Stype','discrete','Nsize',2,'Lpbounds',true, ...
'CSparents',{'FaultyDiagnosis','InadequatePlan','EquipmentFailure', ...
'AmbientConditions'});
```

```
%% Build EnhancedBayesianNetwork objecty
XHumanError=EnhancedBayesianNetwork('Sdescription','human error network', ...
'CXnodes',CXnodes);
XHumanError.makeGraph;

% Marginal Probability Inference, No Evidence
MarginalProbabilities=XHumanError.computeInference('CSmarginal',{
'InadequatePlan', 'ObservationMissed', 'FaultyDiagnosis', 'WrongReasoning',
'Distraction'},'Lbnt',true); % use the BNT (Bayes' Toolbox for Matlab)


 %HEP=human error probability
HEP=XHumanError.computeInference('CSmarginal',{ 'InadequatePlan',
'ObservationMissed', 'FaultyDiagnosis', 'WrongReasoning', 'Distraction'},...
    'Lbnt',true);

% The features below were not used for this Case Study
% Joint Probability Inference, No Evidence
%PlanAndEquipment=XHumanError.computeInference('CSjoint', ...
{'InadequatePlan','EquipmentFailure'},%'Lbnt',false);

% Insert Evidence
%XHumanError.Cevidence{strcmpi(XHumanError.CSnames,'EquipmentFailure')}=2;

%% The new marginal probability once you have inserted the evidence
%MarginalPlan_EquipmentFailureOccured=XHumanError.computeInference('CSmarginal',
{'InadequatePlan','EquipmentFailure'},'Lbnt',false);
```

2.2 Results

The human error probabilities (HEP) of the model on Figure 2 are obtained, as presented in the Figure 3.

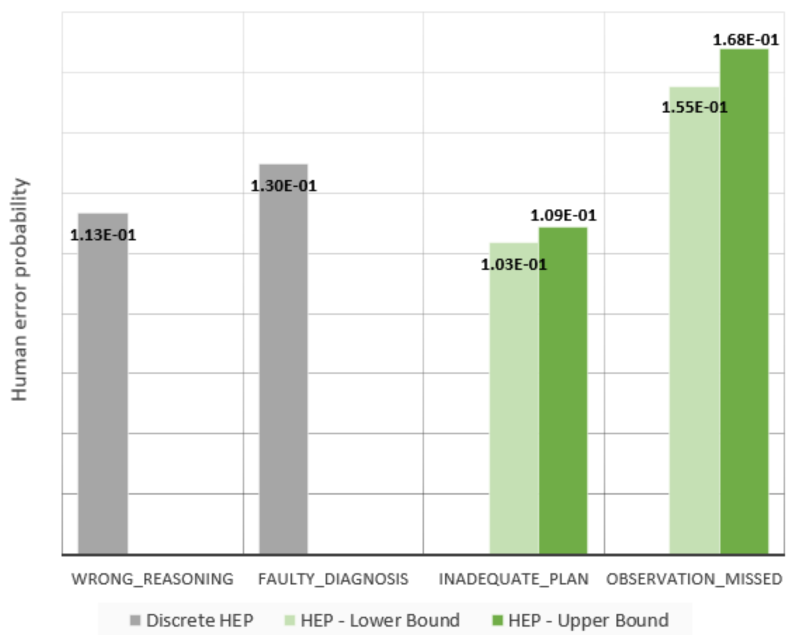


Figure 4: Human error probabilities obtained using the Credal network toolbox

This way, the assessors in the example presented in the beginning of this Case Study, would have to consider as interval for the probability of an operator failing to observe the pressure gauge. Finally, the model also permits comparison of different scenarios, through an what-if analysis. This way, it is possible to know which performance shaping factors have more impact in this type of human error. However, it was not the scope of this case study.

This particular Case Study shows how using the Credal network toolbox can help risk assessors to overcome limitations faced when using the Bayesian networks. Credal Networks have been proposed to integrate Bayesian Networks with imprecise probabilities which, allowing the risk assessors to fully represent the information available from the dataset of major accidents and its uncertainties.

References

Caroline Morais, Raphael Moura, Michael Beer, and Edoardo Patelli. Attempt to predict human failure rate in different industry sectors using data from major accidents and bayesian networks. In *PSAM*, 2018.

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