Exploring uncertainty in quantitative risk assessment used for decision support in electricity distribution system asset management

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ABSTRACT: There is a trend among electricity distribution companies towards using risk assessment for asset management decision support. This paper highlights some aspects of exploring uncertainty in risk analyses, through using reliability importance measures, sensitivity analyses and Monte Carlo simulations. The approaches are exemplified in a case analyzing potential oil spill from distribution transformers. The case illustrates that risk analysis results are not objective, crisp values – but uncertain figures which are more or less sensitive to changes in risk model input parameters. This is an important aspect to acknowledge when utilising risk analysis results in decision support.

1 INTRODUCTION

In Norway, there is a trend among electricity distribution companies towards using risk assessment for decision support in their asset management – see e.g. (Nordgård et al. 2005; Istad et al. 2008). The distribution company risks cover many consequence categories, incorporating tangible as well as intangible risks, e.g. safety, quality of supply (including reliability), environmental impact and economy (Sand et al. 2007).

Historically, risk assessment methods concerning reliability analyses in power systems have been given much attention, with numerous methods available and still being developed – see e.g. (Billinton et al. 2001; Xie & Billinton 2009).

However, for the other risk consequence categoriesthere has been a lack of structured analyses available. The electricity distribution companies therefore see the need to develop methods and tools to support decisions also within these areas. Risk analyses (for other purposes than reliability analyses) are hence being developed, tried and evaluated – see e.g (Hamoud et al. 2007; Nordgård 2008; Nordgård & Sand 2008).

This paper shows how quantitative risk assessment (QRA) can be applied to analyze intangible risks, with special emphasis on approaches for including uncertainty in the analyses. It first gives a brief description of risk and uncertainty in electricity distribution – stating the basis for how we look at uncertainty in this context. It further presents three approaches for exploring uncertainty in QRA. The approaches are exemplified through a case where a bow-tie model is used to analyze environmental risk related to accidental emissions of transformer oil. The paper concludes with some remarks concerning what can be achieved through exploring uncertainty explicitly in risk analyses.

2 RISK-INFORMED DECISION MAKING IN ELECTRICITY DISTRIBUTION

2.1 *Risk decision problems*

Almost every activity will include risk, and even though striving to reduce it, it will be impossible to achieve a complete elimination of risk. Hence we will always face the problem of what is acceptable risk (Fischhoff et al. 1981; Vatn 1998).

In electricity distribution asset management, we want to use risk assessment as a tool to analyze risk, to provide increased understanding of the risk problem and to structure and document the results. The aim is to provide input to the decision making process, where the acceptable risk problem is addressed.

2.2 *Uncertainty*

Uncertainty – the fact that there are things that we do not know – is a prerequisite for risk, and should be kept in mind throughout risk assessment and decision making.

Like ‘risk’, the term ‘uncertainty’ is used with different interpretations in the risk analysis society. In some contexts a distinction is made between decision made under uncertainty (meaning decision situations with unknown probability distributions), and decision made under risk (meaning decision situations with known probability distributions).

If we should have used this terminology for decision making concerning intangible risk in electricity distribution systems, we would most probably be talking about 'decisions under uncertainty' – since the knowledge and data available rarely will provide known probability distributions. However, the broadly accepted term for such analyses is *risk analyses*, and hence we shall use this term in this paper.

In other contexts we encounter the distinction between *aleatory* uncertainty (due to the stochastic nature of a process or system) and *epistemic* uncertainty (due to our lack of knowledge) – see e.g. (Stamatelatos et al. 2002). This distinction can be useful to recognize the fact that even with 'perfect' information available, there will still be uncertainty related to our decisions – i.e. that the decision making process will not converge into a deterministic analysis no matter the extent of our knowledge.

For the purpose of this paper we will not elaborate further on distinction between the two conceptual parts of uncertainty, and will address uncertainty in a common term – representing the fact that *we do not know*, focusing on uncertainty in risk analysis input parameters. This use of the term is in line with e.g (Aven 2008).

2.3 *Setting the scene for distribution system asset management*

The decision maker(s) in distribution system asset management will typically be the asset manager(s) in the companies. Decision support is needed to address risk in a structured manner.

One challenge when analyzing intangible risks within electricity distribution is that there is little experience with such analyses, and hence a lack of analyzing competence.

Another challenge is the availability of data to use in the risk analyses. Our experience indicates that relevant historical data are hard to find when addressing intangible risks (Nordgård et al. 2005). Promoting the hunt for data is a task that should also be addressed in the years to come, but we can not sit around waiting for "hard data" to arrive, because decisions still have to be made.

Expert judgment will hence be the input we can rely on, representing the best available knowledge based on system understanding and experience (Apostolakis 2004; Nordgård 2008).

The input from distribution company experts may e.g. be elicited as:

- "My best guess is that there is a 5-10% change for a failure on this component during the next year. But it might as well be twice this number."
- "I think that the introduction of this barrier will almost eliminate the chance of the most severe consequences – let's say a barrier efficiency of 95-100 %."

With this type of statements as basis for estimating numerical input to the risk analyses, there is an apparent need to investigate the "what-if's" - i.e. to perform analyses where the effects of changing input parameters are investigated and evaluated.

Our aim is to make the uncertainty of expert judgment explicitly included in the risk analysis, making the uncertainties a transparent part of the decision making basis.

2.4 *Quantitative risk assessment as input to decision making*

Risk assessment is a central part of the process of providing input for decision making, and this can be performed using different types of methods - from qualitative to quantitative ones.

In this paper we explore quantitative risk assessment using a bow-tie model to analyze intangible risk – combining fault tree analysis and event tree analysis in order to establish the cause/effect relations describing a specific undesired event, see e.g. (Vatn et al. 1996).

A conceptual bow-tie model is shown in Figure 1.

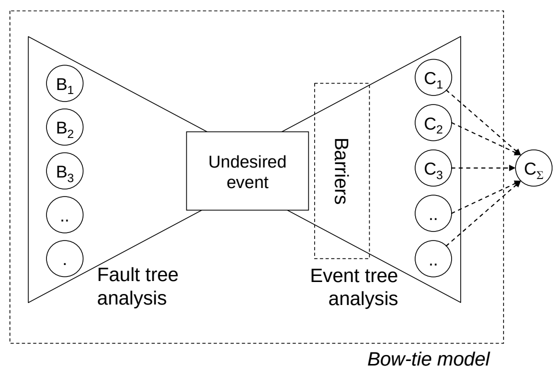

Figure 1 A conceptual bow-tie model.

B_i represents basic initiating events in the fault tree analysis, leading to an undesired event, and C_j represents different possible end events resulting from the event tree analysis. C_Σ are the aggregation of the consequences of all end events into a common risk measure.

2.5 *Methods to explore the effects of uncertainty in risk analyses*

The motivation for exploring the effects of uncertainty in risk analyses, are that we want to see how changes in input parameters will affect the risk analysis results; Will perturbations in input parameters give significant impact on the result? Will the ranking of decision alternatives change as a consequence of this?

In the risk literature there are launched a variety of approaches to investigate the impact of uncertainty in risk analyses – see e.g. (Aven 1992; Aven 2008). Three approaches are described in the following, and exemplified in the case later in this paper, namely:

- Reliability importance measures
- Sensitivity analysis
- Monte Carlo simulations.

The approaches are chosen due to the fact that they represent different ways of addressing the problem requiring different computational efforts.

2.5.1 *Reliability importance measures*

Reliability importance measures can be used in risk analysis to provide information concerning how the system will behave with regards to changes in input parameters. A variety of different measures have been developed. Two classic measures are briefly commented in the following.

Improvement potential

The improvement potential, I^A_i is given by the following equation:

$$I_i^A = h_i - h \tag{1}$$

where h is the reliability of the system and h_i is the reliability assuming that component i is in the best state (Aven 1992).

I^A_i hence expresses the systems improvement potential if element i in the risk model is replaced with a failure-free element.

Birnbaum's measure

Birnbaum's measure of reliability, I^B_i, is given by the following equation:

$$I_i^B = \frac{\partial h}{\partial p_i} \tag{2}$$

To compute I^B_i the following formula is often used:

$$I_i^B = h(1_i, p) - h(0_i, p) \tag{3}$$

where $h(\cdot_i,p) = h(p_1,p_2,..,p_{i-1},\cdot,\ p_{i+1},..,p_n)$ (Aven 1992). I^B_i expresses the system's sensitivity with regards to changes in element i and is hence a measure for how small changes in parameter i will affect the system.

I^A_i and I^B_i can both provide information concerning the robustness of the obtained solutions and where to look for efficient ways of reducing risk.

2.5.2 *Sensitivity analysis*

Sensitivity analysis is performed using performing repetitive analyses where model parameters are changed, to investigate how the changes affects the risk results and hence get information concerning the robustness of the obtained solution.

Results from reliability importance measures can provide input concerning which parameters to investigate closer in sensitivity analyses.

For the purpose of this paper we only look into single parameter sensitivity analyses, i.e. the effects of changing one parameter at the time.

2.5.3 *Monte Carlo simulations*

In Monte Carlo simulations input parameters are represented by probability distributions, and the results are obtained through calculations sampling from these distributions.

Monte Carlo simulation will require higher modelling efforts compared to sensitivity analyses. For the purpose of this paper we look at Monte Carlo simulations where several input parameters are modelled using probability distributions.

In our case, the expert's judgments are translated into probability distributions which again are the basis for parameter sampling in the simulations.

3 ILLUSTRATIVE CASE

We use a case to illustrate the use of methods to explore uncertainty in QRA as input in electricity distribution decision making. The case is based on a quantitative risk assessment model established in (Nordgård & Solum 2009), being further elaborated for the purpose of this paper. It is emphasised that the case is for illustrative purposes only and that it does not represent the decision basis for a real decision.

For the analysis we use a bow-tie model combining fault tree and event tree analysis.

3.1 *Problem description*

Distribution transformers are located throughout the electricity distribution system, containing typically 150-300 litres of oil depending on their size and rating. The oil which is used in the majority of distribution transformers is considered a potential threat to the environment and to human health. The case evaluates environmental and health risk related to potential oil spill from distribution transformers located within the drainage basin of a drinking water reservoir.

3.2 *Numerical input to the risk modelling*

Due to the fact that it is hard to find statistical material which can support the choice of numerical values to use in the modelling, we have to rely on input from expert judgment. All numerical data used in this case study is hence based on the judgment of company experts and the analyst.

3.3 *Fault tree analysis*

Through discussions with company experts two main failure modes have been identified:

- Oil spill due to degradation of the transformer casing, and
- Oil spill due to strokes of lightning destroying the transformer.

With the first failure mode the transformer may still be working, and the oil spill can be detected by inspections. The second failure mode will destroy the transformer. These two failure modes can be modelled in a fault tree as shown in Figure 2, contributing to the top event; "Oil spill from transformer".

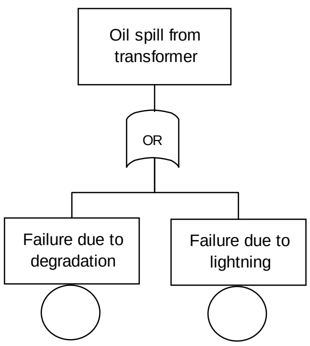

Figure 2 Fault tree - oil spill from transformer.

The following information has been provided by company experts:

- Approximately 1 - 5 out of 1500 transformers have a leakage due to degradation each year.
- Approximately 2 – 3 out of 1500 transformers experience breakage due to lightning strokes each year.

Based on this information the following 'best estimates' are chosen for the fault tree parameters:

- $q_{Degradation} = 2.0 \cdot 10^{-3}$ [events/year]
- $q_{Lightning} = 1.5 \cdot 10^{-3}$ [events/year]

where $q_{Degradation}$ and $q_{Lightning}$ expresses the probabilities for leakage due to casing degradation and lightning respectively.

Assuming independence between the two basic events, the probability of occurrence for the top event is computed according to equation (4):

$$q_{Oil\ spill} = q_{Degrad} + q_{Lightning} - q_{Degrad} \cdot q_{Lightning} \qquad (4)$$

This gives $q_{Oil\ spill} = 0.0035$. Given a case where a company have 25 transformers within a drinking water drainage basin, this gives 0.0875 occurrences of the top event per year - i.e. one can expect the event occurring on average every 11 years.

3.4 *Event tree analysis*

In order to establish the event tree – see Figure 4 – the following barriers are considered, based on discussions with the company experts:

- Whether an oil collector is present
- Whether less than 10 litres of oil leaks
- Whether the transformer is located near a waterway (stream or river) leading directly to the drinking water reservoir.

The amount of oil spilled can not be considered as an ordinary barrier, but rather a statement of possible outcome.

Only substations located on the ground are equipped with oil collectors. The majority of transformers in the area are pole-mounted arrangements, as shown in Figure 3.

Figure 3 Pole-mounted transformer arrangement

The following numerical estimates are chosen for these barriers:

- $q_{Oil\ collector} = 0.9$, i.e only 10 % of the transformers in the area have oil collectors
- $q_{<\ 10\ liters} = 0.8$, i.e. in only 20 % of the cases the oil spill are less than 10 litres
- $q_{Far\ from\ waterway} = 0.6$, i.e. 60 % of the transformers are located near a stream or river leading directly into the drinking water reservoir.

The background for choosing these probability estimates is input from distribution company experts and the analyst.

Based on the previous results from the fault tree analysis, the structure of the event tree in Figure 4 and the probability estimates for the barriers, the results presented in Table 1 are obtained.

We can see that the total expected oil spill within the drainage basin is estimated to be approximately 12.1 litres/years. The most critical event (event 5) – with an oil spill of 250 litres – will expectedly occur every 26 years.

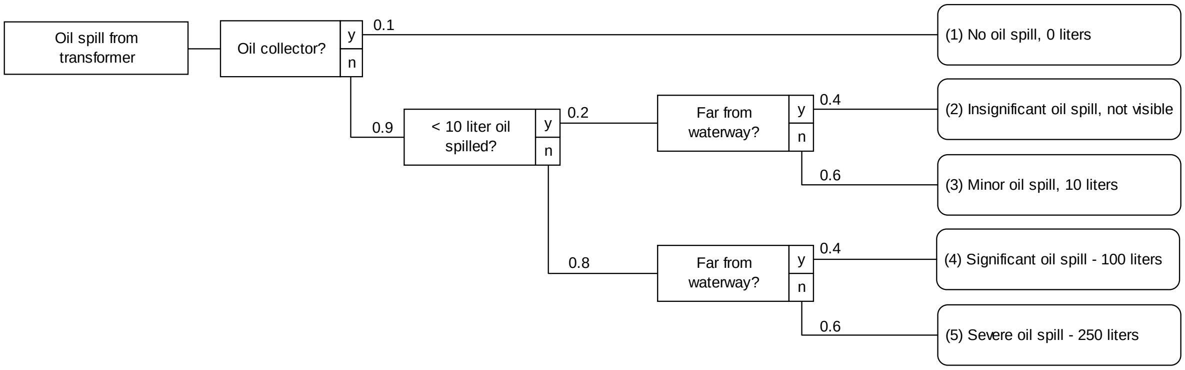

Figure 4 Event tree model for possible outcomes following the start event ‘Oil spill from transformer’

Table 1 Results from the event tree analysis

End event	1	2	3	4	5	*Sum*
Oil spill[1)]	0	1	10	100	250	-
Freq.[2)]	0.009	0.006	0.009	0.025	0.038	-
Time[3)],	114	159	106	40	26	-
E(oil spill) [4)]	0.0	0.0	0.1	2.5	9.5	*12.1*

1) Estimated oil spill of the end event, [Litres]

2) Frequency of occurrence of end event *I* [year^{-1}]

3) Expected time between occurrences [years]

4) Expected annual contribution to oil spill from end event *i* [Litres]

3.5 *Investigating uncertainty in input parameters*

The purpose of investigating the effects of uncertain parameters is to illustrate the effect of the changes in the risk analysis model, and to gain understanding and confidence in the risk analysis results.

3.5.1 *Reliability importance measures*

The risk analysis model is first analysed using importance measures to analyze the impact of changes in the input parameters.

Table 2 Calculated reliability importance measures for the input parameters

Model parameter	Improvement potential, I^A_i	Birnbaum measure I^B_i
$q_{Degradation}$	6.9	3448.8
$q_{Lightning}$	5.2	3448.8
$q_{Oil\ collector}$	12.1	5.7
$q_{<\ 10\ litre}$	11.6	6.2
$q_{Far\ from\ waterway}$	5.8	4.1

The improvement potential is the largest for the model parameter $q_{Oil\ collector}$. It should however be noted that the values for the improvement potential are dependent on the values chosen as the base case reference (the value of *h* in equation (1)).

The Birnbaum measures indicate that the estimated oil spill is clearly most sensitive to the changes in the two fault tree parameters $q_{Degradation}$ and $q_{Lightning}$, but since the failure probabilities here already are very small numbers – the improvement potential is not so large for these parameters.

3.5.2 *Sensitivity analyses*

In order to examine the effects of changing model parameters, sensitivity analyses are performed for low and high estimates for the input parameters. The analyses have been performed by repetitive calculations changing one parameter at the time – seeing how this affects the results. The results for low and high estimates are shown in Table 3, while the ‘best-estimate’ results are given in Table 1.

Table 3 Results from investigating the effects of uncertainty of input parameters – Low and High estimates

	Parameter estimate		Sum annual oil spill, [Litres]	
	Low	High	Low	High
$q_{Degradation}$	$1.0 \cdot 10^{-3}$	$3.0 \cdot 10^{-3}$	8.6	15.5
$q_{Lightning}$	$1.33 \cdot 10^{-3}$	$1.67 \cdot 10^{-3}$	11.5	12.7
$q_{Oil\ collector}$	0.85	0.95	11.4	12.7
$q_{<\ 10\ litres}$	0.6	1.0	9.2	15.0
$q_{Far\ from\ waterway}$	0.5	0.7	11.1	13.0

The variation in results (best estimates from Table 1, and Low/high estimates from Table 3) are illustrated in Figure 5.

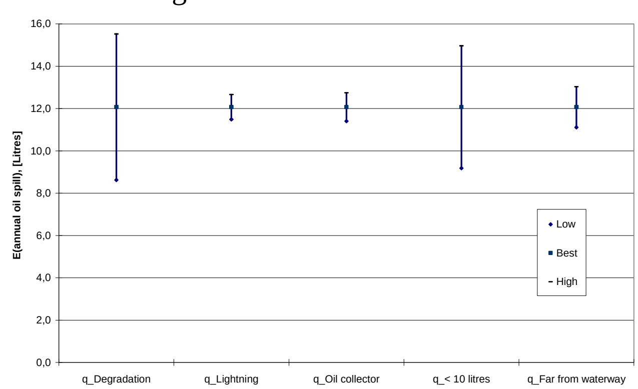

Figure 5 Variation of E(annual oil spill) for low / best / high parameter values

Figure 5 indicates that the largest variation is found for the high/low estimates for the parameters $q_{Degradation}$ and $q_{<10\ litres}$.

3.5.3 *Monte Carlo simulation*

A Monte Carlo simulation model is established to investigate the effect of simultaneous variation of input parameters.

The simulation model is made using triangular distributions for the five input parameters stated in Table 3 with mean values equal to the best estimates and low and high values (Table 3) giving the low and high ends of the probability distributions.

Results from a simulation of estimated annual oil spill are shown in Figure 6. The simulation was made using 1000 iterations sampling from the above given distributions for the five input parameters.

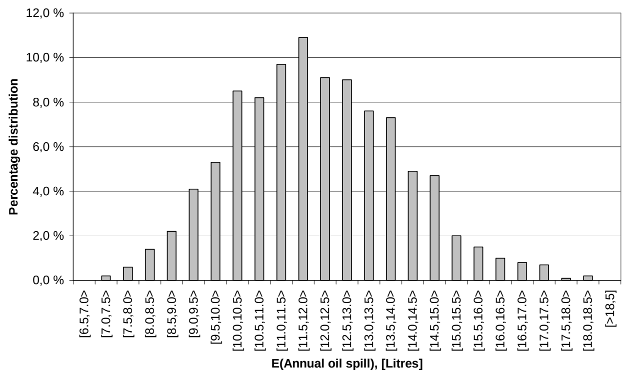

Figure 6 Monte Carlo simulation results of annual oil spill

The centre of gravity for the results corresponds to the expected value we have computed earlier (12.1 litres/year), but we have a widespread variation of results around this value – wider than what is obtained when varying only one parameter at the time, as done in the sensitivity analysis.

We can see from the results that the sensitivity analyses and the Monte Carlo simulations give a more balanced risk picture compared to only the expected values stated in Table 1.

3.5.4 *Evaluation of the initial results*

To evaluate the results – we use a taxonomy proposed in (Wessberg et al. 2008) to evaluate the consequences of potential accidental emissions. The taxonomy uses three consequence categories for ground water / water intake:

- Moderate. No harm to water intake
- Extensive: Water intake is temporarily prevented
- Serious: Water intake is prevented for the long-term

Table 4 shows the risk categorisation.

Table 4 Risk matrix – risk categorisation – *based on Table 3 (Wessberg et al. 2008)*

	Moderate	Extensive	Serious
5 - More than once a month	II	I	I
4 - More than once a year	II	I	I
3 - More than once in 10 years	III	II	I
2 - Once in a lifetime[1)]	IV	III	II
1 - Situation is known[2)]	IV	IV	IV

1) The lifetime of the industrial site

2) It has happened sometimes somewhere

The risk categories in Table 4 are classified as follows (Wessberg et al. 2008):

- I: Risk elimination actions must be started immediately
- II: Risk reduction needed. Proposals for actions as soon as possible.
- III: Proposals for actions to risk reduction should be given within a year.
- IV: No actions needed

The estimated expected consequence for our case is regarded to be in the categories *Moderate* to *Extensive*, while the probability of occurrence is in categories 2 – 3. The investigated uncertainty in the risk results supports the choice of these categories.

We can draw the conclusion that the risk can not be considered unconditionally acceptable, and proposals for risk reduction should be considered – but that there is no need for immediate action.

3.6 *Decision alternatives*

To address this problem further the following decision alternatives have been identified for the risk analysis as means to reduce risk:

- Alternative 1: Leave as is. (basis alternative)
- Alternative 2: Redesign of transformer arrangements to include oil-collectors.
- Alternative 3: Relocation of transformers – location further away from waterways.
- Alternative 4: Redesign of transformer earthing system – making it less exposed to lightning strokes.
- Alternative 5: Replace transformers with new design with environmentally friendly insulating oil. This alternative is regarded to eliminate the negative consequences from oil spill.

The model parameters chosen for the alternatives are stated in Table 5, and the expected values of annual oil spill for the chosen alternatives are illustrated in Figure 7.

Table 5 Model parameters used for the different alternatives*

	Parameter estimates Alt. 1	Alt. 2	Alt. 3	Alt. 4
$q_{Degradatio}$	$2.0 \cdot 10^{-3}$	$2.0 \cdot 10^{-3}$	$2.0 \cdot 10^{-3}$	$2.0 \cdot 10^{-3}$
$q_{Lightning}$	$1.5 \cdot 10^{-3}$	$1.5 \cdot 10^{-3}$	$1.5 \cdot 10^{-3}$	$0.5 \cdot 10^{-3}$
$q_{Oil\ collector}$	0.9	0.1	0.9	0.9
$q_{<\ 10\ litre\ oil}$	0.8	0.8	0.8	0.8
$q_{Far\ from\ waterway}$	0.6	0.6	0.1	0.6

* *Alternative 5 eliminates the environmental impact of the transformer oil. The system reliability parameters for alternative 5 remain unchanged – i.e. equal to alternative 1.*

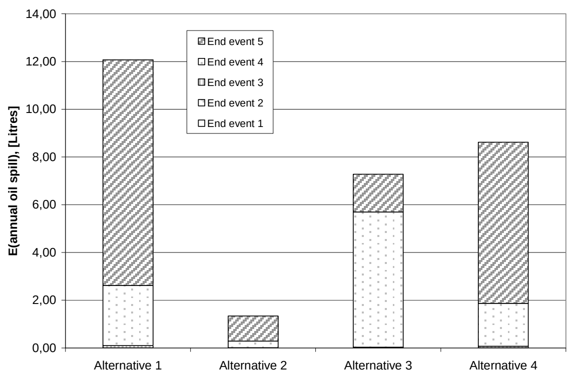

Figure 7 E(annual oil emissions) for Alternatives 1-4 with partial contribution from the different end events.

The different alternatives can also be investigated with sensitivity analyses too see how the changes in parameter estimates will affect the results.

Figure 8 shows an example on how changes in one parameter – in this case $q_{Lightning}$ – influences the estimated expected annual oil spill.

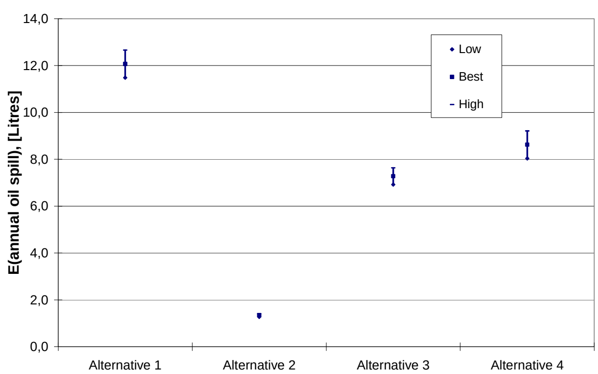

Figure 8 E(annual oil emissions) for Alternatives 1-4 for low, best and high estimates of $q_{Lightning}$.

The analysis clearly indicates that alternative 2 is the most efficient one with regards to risk reduction.

3.7 *Comments to the case*

The case illustrates some possibilities of exploring uncertainty in input parameters in a quantitative risk assessment model.

The purpose of performing such analyses should be to provide the decision maker with information concerning the robustness of his or hers risk analysis results. It should also be emphasised that the risk analyses will provide indicative rather than absolute answers as illustrated by the results from the case.

The risk analysis results should further be brought into a decision making process, where other aspects such as cost, reputational impact, etc. should also be included. The uncertainty in the risk analysis results should also be taken into account in the final decision making process.

The final decision making process is not further elaborated in this paper. An example on how such decision support can be performed can e.g. be found in (Catrinu & Nordgård 2009).

4 CONCLUDING REMARKS

This paper has presented three different methods for how uncertainty in input parameters can be explored in quantitative risk analysis and how the results can be used to provide decision support.

For the purpose of providing decision support in relatively simple QRA models in electricity distribution system asset management, sensitivity analysis will provide an efficient way to give useful information with a relatively low computational effort. Reliability importance measures can be used to give direction of where to look for risk reducing measures, but it should be accompanied with sensitivity analysis to illustrate the effect of the changed parameters. Monte Carlo simulation will give a broader risk picture, but it will demand more sophisticated modelling, and the results provided will not give significantly more information compared to sensitivity analyses.

What should be emphasised when exploring uncertainty in QRA is highlighting the fact that risk analysis results are not objective, crisp values – but uncertain figures which are more or less sensitive to changes in model input parameters.

We see that the results based on 'best estimates' will represent only part of the risk picture which the decision maker should be aware of.

In practical application, a realistic ambition is to use risk analysis to increase the understanding of the risk problem, and to provide input to risk-informed decisions. It should be kept in mind that also other input than risk analyses are relevant in the decision making context. The risk analysis should hence never be the sole basis for making decisions, but rather contribute to making decisions risk-informed (Apostolakis 2004). Exploring uncertainty is an important part of this task.

5 ACKNOWLEDGEMENTS

The author would like to thank Geir Solum and Alf Karlsvik at Trondheim Energy for initial discussions and input concerning the case study.

The work reported in this paper has been performed as part of the research project ‘Risk Based Distribution System Asset Management’ at SINTEF Energy Research. The author thanks the project consortium for funding the activities.

The thorough comments from the anonymous reviewers are also highly appreciated.

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