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# Accounting for uncertainties due to high-impact low-probability events in power system development

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ABSTRACT

In the long-term development of the electric power system, system operators should consider the socio-economic balance between grid investment costs and security of supply, including the risk of power supply interruptions. Cost-benefit analyses conducted for this purpose are associated with many uncertainties but have traditionally focused on the expected value of the net socio-economic benefits of risk-reducing measures. This article focuses on the large uncertainties that are associated with the possible occurrence of high-impact low-probability interruption events (HILP events). The objective is to quantify and visualize the implications of uncertainties due to HILP events in the context of power system development. More specifically, this article describes a methodology accounting for uncertainties in socio-economic cost-benefit analysis of measures for reducing the risk of HILP events. The methodology accounts for the contributions of both aleatory and epistemic uncertainties and comprises a hybrid probabilistic-possibilistic uncertainty analysis method. Applying the methodology to a real case involving a grid investment decision, it is demonstrated how it provides additional insight compared to conventional cost-benefit analyses considering expected values where uncertainties are not accounted for explicitly. It is furthermore discussed how these results can help to better inform grid development decisions.

## 1. Introduction

For an electric power transmission system, system development involves activities carried out by the transmission system operator (TSO) to ensure safe system operation, provide a high level of security of supply and contribute to the socio-economic efficiency of the system [1]. It is a part of long-term power system planning, considering planning horizons up to several decades into the future, and involves choices between different grid investment alternatives. Grid investment costs can be substantial and are ultimately socialized to the end user through the grid tariffs. Several countries have introduced interruption costs in their quality of electricity supply regulation to achieve a better socio-economic balance between grid costs and security of supply. To use Norway as an example, a cost of energy not supplied (CENS) scheme is implemented by which interruption costs are estimated and deducted from the grid companies' revenue caps [2–5]. The Norwegian TSO Statnett is required by law [6] to develop the transmission grid in a socio-economic rational manner. Recently, Statnett has moreover implemented new guidelines for assessing security of supply in power system planning. According to these guidelines, the TSO shall 1) describe risk of power supply interruptions for all grid development alternatives, 2) monetize security of electricity supply as far as possible in their socio-economic cost-benefit analyses, and 3) quantify to the extent possible the relevant uncertainties. Traditionally, such cost-benefit analyses have focused on expected values of interruption costs as an approximation for their societal costs. Historically, the risk of power supply interruptions may even not have been quantified at all. In either case, uncertainties were not explicitly considered in the cost-benefit analysis. A comprehensive description of risks is important to inform long-term system development decisions, and there is thus a need for new and improved methods to account for uncertainties.

This article is concerned with a specific subset of uncertainties related to security of supply, namely uncertainties due to the possible occurrence of high-impact low-probability (HILP) events. This term refers to extraordinary events in the power system with high societal consequences (or impact) to society and thus high socio-economic costs [7–9]. Examples of such events include major blackouts due to extreme weather, due to other natural hazards, or due to more diverse and complex causes [8,10–12]. The associated uncertainties are very high because of the lack of knowledge about the likelihood that such events

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may occur and also about their actual societal impact if they do. The objective of this work is to quantify and visualize the implications of uncertainties due to HILP events in the context of power system development. The purpose is to better inform system development decisions by comprehensively describing risk and uncertainty.

In general, one can distinguish between *aleatory uncertainty,* which represents random or stochastic variation, and *epistemic uncertainty*, which represents uncertainty due to lack of knowledge [13]. One can argue that since HILP events are unique or extremely rare events, they are intrinsically associated with large epistemic uncertainties [14]. This has been acknowledged in the general risk assessment literature, and it is argued that a weak knowledge basis makes it difficult to justify a probabilistic uncertainty analysis [13,15,16]. It has furthermore been argued that a *possibilistic* approach to uncertainty analysis may be a more appropriate approach for such epistemic uncertainties [13,17].

Estimates of the risk of HILP events will be associated with both aleatory and epistemic contributions to uncertainty, as exemplified later in this article. It is therefore important to capture both types of uncertainties in the analysis. Purely possibilistic or fuzzy representation of uncertainty in power system risk assessment applications has a long history, see e.g. [17,18] and references therein. One relevant example for our work is [19], which compares different risk-averse operating criteria to a fuzzy representation of failure rate uncertainty. General mathematical methods for accounting for uncertainty in power system analysis, including probabilistic methods, possibilistic methods, and hybrid methods that combine probabilistic and possibilistic representations of uncertainty, are reviewed in [20–23]. However, the reviews do not focus on risk assessment, and none of the reviewed works consider the risk assessment of HILP events. Ref. [14] describes the development of a qualitative framework for analysing HILP events in the context of different power system decisions. This framework includes characterizing and accounting for relevant uncertainties, but methods for quantitative analysis of uncertainties were left for future work.

Different hybrid probabilistic-possibilistic uncertainty analysis methods have previously been applied to power systems risk analysis in e.g. [18,24,25] to account for both aleatory and epistemic uncertainty. References [18,25] apply such methods in the context of power system reliability analysis to quantify the uncertainty in estimates for energy not supplied. Reference [24] presents a method that is applied to quantify the uncertainty in metrics for the power system's vulnerability to transmission line failures. Still, none of these works focus on HILP events, and none of them are set in the context of power system development decisions or involve cost-benefit analyses. More relevant work on combined probabilistic-possibilistic analysis of the risk of HILP-like events is reported in the general risk assessment literature [26,27]. To the best of our knowledge, such methods have not previously been applied to HILP events in power systems.

In this article, we build upon previous research outlined above and extend methodologies for uncertainty analysis to power system development decision problems involving possible HILP events. One probabilistic approach to this problem would be to balance the expected interruption costs of HILP events against the cost of risk-reducing grid investment measures using a socio-economic cost-benefit analysis framework as described in e.g. [19,28–30]. However, questions have been raised in the risk assessment community of whether cost-benefit analysis alone is appropriate for decision making under uncertainties so severe as is the case with HILP events [31,32]. Moreover, the dependency on expected values has been seen as problematic [33]. The main contributions of the present article to the research literature can be stated as follows:

1 Formulating the problem of accounting for uncertainties due to HILP events in the context of socio-economic cost-benefit analysis for power system development. This is, to the best of our knowledge, the first time this problem has been described and addressed in the research literature.
2 Proposing a novel application of hybrid possibilistic-probabilistic uncertainty analysis methods to the above problem, quantifying the implications of uncertainties relevant for HILP events. The novelty lies in the techniques proposed for visualizing the implications of the uncertainties to power system development and in incorporating socio-economic cost-benefit analysis, and the methodology also extends previously published work by including Latin Hypercube Sampling and a surrogate model in the uncertainty analysis.
3 Applying the methodology to a real case, illustrating thus the additional insights that TSOs can gain compared to considering only expected values in system development decisions. This comprehensive case study was carried out in close collaboration with the Norwegian TSO and considers a concrete case where the TSO considers investing in an additional transmission line to reduce the risk of HILP events.

The rest of the article is structured as follows. Section 2 introduces the necessary preliminaries of a socio-economic cost-benefit analysis for power system development decisions and presents the proposed uncertainty analysis methodology. The methodology is exemplified by applying it to a concrete case study in Section 3. Here, the uncertainties appearing in the cost-benefit analysis are quantified and visualized, and emphasis is put on illustrating how different visual representations may provide additional insight into the decision problem. The implications of applying this methodology for power system development decision making are discussed in Section 4, before the article is concluded in Section 5.

## 2. Methodology

To simplify the presentation of the methodology we will in this section consider the choice between two generic power system development alternatives: The costs and benefits of *risk-reducing measures* considered to reduce the risk of HILP events (alternative B) are compared to a reference alternative (or *zero alternative*) without such measures (alternative A). Concrete examples of such system development alternatives are illustrated in the case study in Section 3. Implementing risk-reducing measures is, without lack of generality, assumed to reduce the frequency of occurrence of HILP events from $\lambda$ to $(1 - f_{\mathrm{red}})\lambda < \lambda$. How the baseline frequency $\lambda$, the reduction factor $f_{\mathrm{red}}$, and other parameters related to the HILP event can be estimated will depend on the case and is not the focus of the methodology presented here. Instead, the methodology intends to contribute to answering the following: Given that the TSO needs to make a system development decision, and given some estimates for parameters relevant to the decision and their uncertainties, how can this information about what is known or not known to the TSO be used to support decision making?

The proposed uncertainty analysis methodology is outlined step by step below:

1 Socio-economic cost-benefit analysis including interruption costs: This is the starting point that the proposed uncertainty analysis is building upon and is first presented in Section 2.1 without considering uncertainties.
2 Probabilistic uncertainty analysis: Simulations to estimate the risk of HILP events, accounting for only aleatory uncertainties and using fixed values of parameters with epistemic uncertainty, are described in Section 2.2 (as an inner loop of a double-loop Monte Carlo method).
3 Hybrid possibilistic-probabilistic uncertainty analysis: Method accounting also for epistemic uncertainties (as an outer loop of a double-loop Monte Carlo method) is presented in Section 2.3, quantifying and visualizing uncertainties in the form of possibility distributions and probability bounds.

The flowchart in Fig. 1 illustrates schematically the methodology

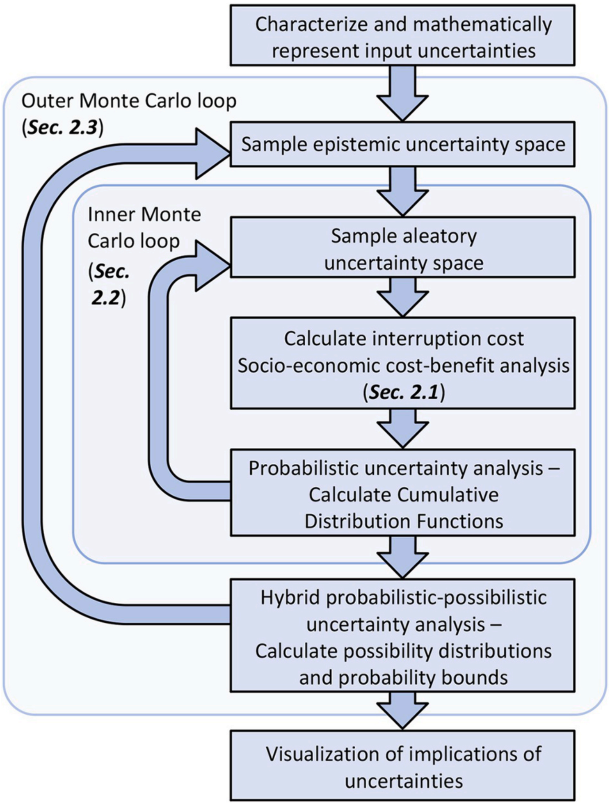


**Fig. 1.** Schematic illustration of the proposed methodology.

including the double-loop Monte Carlo method and how the different steps are related. Each step of the methodology is also applicable to non-HILP events, but as explained in Section 3, the value of including possibilistic uncertainty representation (Step 3) is greater when there are large epistemic uncertainties, such as for HILP events.

### 2.1. Socio-economic cost-benefit analysis including interruption costs

Investment decisions choosing between different grid development alternatives should be based on a socio-economic cost-benefit analysis accounting for the risk of power supply interruption events for the alternatives. This section describes the basic formulation for such an analysis for general interruption events, and then application to HILP events and their uncertainties is considered in the following. Typically, an estimate for the societal costs associated with interruption events is quantified in monetary terms as the expected annual interruption cost $\mathrm{IC_a}$. This can be understood as a measure of the risk associated with the interruption event and can in its simplest form be expressed as follows:

$$\mathrm{IC_a} = \lambda \cdot r \cdot P_{\text{interr}} \cdot c. \tag{1}$$

This equation expresses the long-term average interruption cost (in NOK per year) as a function of the frequency of occurrence $\lambda$ of the event (per year), the average interrupted power $P_{\text{interr}}$ during the event (MW), the average interruption duration $r$ (hours) and the average specific interruption cost $c$ for end-users affected by the event (NOK/MWh).

The cost-benefit analysis is based on discounting all socio-economic cost contributions over an extended analysis horizon to the present and calculating the present value. We denote the present value of the total socio-economic costs by the *total costs*, TC, which can be calculated as

$$\mathrm{TC} = C + \mathrm{IC} = C + \sum_{y=1}^{y_{\text{end}}} \frac{\mathrm{IC}_y}{(1+f_{\text{d}})^y}, \tag{2}$$

where $y$ is the number of the year in the analysis horizon and $f_{\text{d}}$ is the discount rate. IC denotes the present value of the interruption costs, and $C$ is the grid investment costs, which is assumed to be incurred in year $y = 0$. The analysis horizon is denoted by $y_{\text{end}}$.

Eq. (2) neglects several of the socio-economic benefits that are considered in the socio-economic cost-benefit analysis ordinarily carried out by the TSO, such as e.g. reduction in grid losses and reduction in congestion costs [28,29]. We omit these terms here to simplify the presentation and to focus on the key contributions in this work, namely the risk associated with possible HILP events. Moreover, differences between the grid development alternatives for these contributions were negligible in the case that is presented in Section 3. The total socio-economic impact or net present value (benefits minus costs) of risk-reducing measures when comparing to zero alternative can then be expressed as

$$\Delta\mathrm{TC} = \mathrm{TC_B} - \mathrm{TC_A}. \tag{3}$$

For brevity, we will henceforth refer to $\Delta$TC as the *net socio-economic benefit*. When estimating the interruption costs in a given year $y$ in the future, we have to account for the expected growth in load demand, which determines the power $P_{\text{interr},y}$ that is potentially interrupted. In addition, we should also account for a possible increase in the specific interruption cost $c_y$. The time development for both parameters will be modelled assuming constant annual growth rates $f_P$ and $f_c$ as follows:

$$P_{\text{interr},y} = P_{\text{interr},y=0}(1+f_P)^y, \tag{4}$$

$$c_y = c_{y=0}(1+f_c)^y. \tag{5}$$

### 2.2. Probabilistic uncertainty analysis

This section describes probabilistic simulations for estimating the risk of HILP events, accounting for aleatory uncertainties as the inner loop of a double-loop Monte Carlo (MC) method. The inputs assumed for these simulations include probability distributions for interruption duration $r$ and for grid investment costs $C_{\text{A}}$ and $C_{\text{B}}$ for the reference alternative and for risk-reducing measures, respectively, and an hourly time series of the load $P(t)$ potentially interrupted in case of a HILP event. The specific interruption cost $c$ is assumed to be described by a function $c(t,r)$ of the interruption duration $r$ and the time of occurrence $t$. Epistemic uncertainties are for the time being neglected but will be considered in Section 2.3. The methodology follows a basic Monte Carlo approach where we run a large number $N_{\text{MC}}$ of MC simulations of the $y_{\text{end}}$-year analysis horizon. For each simulation, we draw pseudo-random numbers to simulate the possible occurrence of HILP events, and we estimate the interruption costs due to HILP events, both when assuming the zero alternative (A) and when assuming that risk-reducing measures have been implemented (B).

We model the occurrence of a HILP event during a given year as a Bernoulli experiment with a probability

$$p = 1 - e^{-\lambda\Delta t} \approx \lambda\Delta t \tag{6}$$

for alternative A, where the period $\Delta t = 1$ year. For alternative B, only a fraction $(1 - f_{\text{red}})$ of the events sampled in this manner are modelled as occurring. For each sampled HILP event, pseudo-random numbers are generated for parameter triplets $(P_{\text{interr}}, r, c)$. First the time (hour) of occurrence $t$ is sampled from a uniform distribution over the range of $t$ values that the hourly load input time series $P(t)$ is defined for, and the interruption duration $r$ is sampled from its probability distribution. The average interrupted power is then calculated as

$$P_{\text{interr}}(t,r) = \frac{1}{r}\sum_{t}^{t+r-1} P(t). \tag{7}$$

The average specific interruption cost $c$ for the event is calculated from the function $c(t,r)$. In the case study in Section 3, this is exemplified using the Norwegian CENS scheme as described in the Appendix. In this manner, time-dependant correlations between $r$, $P_{\text{interr}}$ and $c$ are captured in the analysis [17,34]. For each year, the interruption cost is estimated according to $\text{IC}_y = P_{\text{interr},y} \cdot r \cdot c_y$, where (4) and (5) have been used to account for the year of occurrence.

For a given MC iteration, the total present value of the interruption costs over the analysis horizon for grid development alternatives ($\text{IC}_\text{A}$ and $\text{IC}_\text{B}$) is then calculated using (2). The probability distributions of these interruption costs are then estimated based on the $N_{\text{MC}}$ realizations from the MC simulation in the form of cumulative distribution functions (CDFs) $F(\text{IC}_\text{A})$ and $F(\text{IC}_\text{B})$. Similarly, an estimate is made for the probability distribution $F(\Delta\text{TC})$ of the net socio-economic benefit of the risk-reducing measures.

The estimated probability distributions can be used to derive the expected value $\mathbb{E}(\text{IC})$ of the interruption cost. To quantitatively assess the high-impact tail of the probability distribution for IC, the Value-at-Risk will also be considered. The Value-at-Risk at level $\gamma$, $\text{VaR}_\gamma(\text{IC})$, is a risk measure that is implicitly defined by the relation $F(\text{VaR}_\gamma(\text{IC})) = 1 - \gamma$ and corresponds to the $(1 - \gamma)\cdot 100\%$ percentile of the distribution for IC.

### 2.3. Hybrid probabilistic-possibilistic uncertainty analysis

In contrast to the probabilistic representation, a possibilistic uncertainty representation does not assume the existence or knowledge of any probability distribution for the value of the uncertain parameter. Instead, it is based on a *possibility distribution* representing the degree of possibility (*not* probability) of the parameter. We use the notation $\pi(x)$ for the possibility distribution function for a general variable $x$, where $0 \leq \pi(x) \leq 1$. If $\pi(x) = 0$ for a value of $x$, this means that this outcome of $x$ is impossible. On the other hand, $\pi(x) = 1$ simply means that this outcome of the value of $x$ is *possible*. All values of $x$ with $\pi(x) > 0$ would also be possible to some degree, and we denote the set of these values as $A_x$.

In a possibilistic uncertainty analysis, uncertainties can be propagated using a method based on so-called *α-cuts* [13,20,21,23]. For a variable $x$, the *α-cut* $A_{x,\alpha} \subseteq A_x$ is defined as

$$A_{x,\alpha} = \left[x_\alpha^-, x_\alpha^+\right] = \{x \in \mathbb{R} \mid \pi(x) \geq \alpha\}. \tag{8}$$

The uncertainties that are represented in possibilistic terms define an *epistemic uncertainty space* $\boldsymbol{A} \equiv A_{x_1} \times \ \ldots \ \times A_{x_N}$. This is a hyper-rectangle that defines the region of the parameter space that is considered possible for these uncertain parameters.

The proposed hybrid probabilistic-possibilistic uncertainty analysis is based on a double-loop Monte Carlo method for propagating aleatory and epistemic uncertainties. This double-loop MC method was inspired by [24] and is illustrated in Fig. 1: The outer loop samples a set $\boldsymbol{S_x}$ of possible realizations $\boldsymbol{x}$ from the epistemic uncertainty space $\boldsymbol{A} \equiv A_{x_1} \times \ldots \times A_{x_N}$; for each realization $\boldsymbol{x} \in \boldsymbol{S_x} \subset \boldsymbol{A}$, the inner loop samples $N_{\text{MC}}$ realizations of the interruption costs of HILP events from the aleatory uncertainty space using the probabilistic uncertainty analysis as described in Section 2.2. The double-loop method thus generates a set of CDFs $F_{\boldsymbol{x}}(Y)$ for each realization $\boldsymbol{x} \in \boldsymbol{S_x}$ of epistemic uncertainty. Here, $Y$ can represent any of the socio-economic quantities defined in Section 2.1, and the CDF $F_{\boldsymbol{x}}(Y)$ describes the aleatory uncertainty in $Y$ for a given value of $\boldsymbol{x}$.

We then introduce $Z(\boldsymbol{x})$ to denote any uncertain quantity derived from the CDFs $F_{\boldsymbol{x}}(Y)$ that depends on the realization of epistemic uncertainties $\boldsymbol{x}$. This can be used to represent both the value of $F_{\boldsymbol{x}}(Y)$ as a function of $\boldsymbol{x}$ for a fixed value of $Y$, and to represent the expected value $\mathbb{E}(Y)$ as a function of $\boldsymbol{x}$ that is obtained by integrating over all values of $Y$. The expected socio-economic cost for the zero alternative, $Z(\boldsymbol{x}) = \mathbb{E}(\text{TC}_\text{A})$, is an example of such a statistic for the case that $Y = \text{TC}_\text{A}$. The outputs of the methodology described below will be possibility distributions $\pi(Z)$ that represent the epistemic uncertainty in $Z$ and probability bounds, also referred to as p-boxes [24], which visually describe the contributions of aleatory and epistemic uncertainty for an uncertain quantity $Y$.

In the methodology we first need a set of samples $\boldsymbol{S_x}$ from the epistemic uncertainty space in the outer loop. From the possibility distributions $\pi(x_i)$ we construct $M$ $\alpha$-cuts for each input parameter $x_i$. These will be denoted $A_{x_i,\alpha_j}$ and calculated for the set of $\alpha$ values $\{\alpha_1 = 0, \alpha_2, \ldots, \alpha_M = 1\}$ using (8). We then let $\boldsymbol{A}_{\alpha_j} \in \mathbb{R}^N$ denote the hyper-rectangle formed by the $j^{\text{th}}$ $\alpha$-cut for the $N$ individual variables in $\boldsymbol{x}$:

$$\boldsymbol{A}_{\alpha_j} = A_{x_1,\alpha_j} \times \ \ldots \ \times A_{x_N,\alpha_j} = \left\{\boldsymbol{x} \mid x_1 \in A_{x_1,\alpha_j} \ \wedge \ldots \wedge \ x_N \in A_{x_N,\alpha_j}\right\}. \tag{9}$$

To propagate the uncertainties in the input parameters $x_1, \ldots, x_N$ to the resulting uncertainty in $Z$, we calculate $M$ $\alpha$-cuts $A_{Z,\alpha_j} = [Z_{\alpha_j}^-, Z_{\alpha_j}^+]$ for $Z$ for each $\alpha_j \in \{\alpha_1, \ldots, \alpha_M\}$. To do so we need to find the lowest and highest values of $Z$ possible for any $\boldsymbol{x}$ within the hyper-rectangle $\boldsymbol{A}_{\alpha_j}$ [13,20,24]:

$$\left[Z_{\alpha_j}^-, Z_{\alpha_j}^+\right] = \left[\min_{\boldsymbol{x} \in \boldsymbol{A}_{\alpha_j}} Z(\boldsymbol{x}), \max_{\boldsymbol{x} \in \boldsymbol{A}_{\alpha_j}} Z(\boldsymbol{x})\right]. \tag{10}$$

The possibility distribution $\pi(Z)$ is then constructed from this set of $\alpha$-cuts for $Z$. Probability bounds are constructed for each value of $Y$ by considering the $\alpha$-cut for $\alpha_{j=1} = 0$. This corresponds to finding the upper and lower bounds on $F(Y)$ for the set of all possible CDFs $F_{\boldsymbol{x}}(Y)$.

To estimate the $\alpha$-cuts in Eq. (10) we propose the following samples $\boldsymbol{S_x}$: The set of vertices of the hyper-rectangles $\boldsymbol{A}_{\alpha_j}$ are first sampled for all $M$ $\alpha$-cuts. This amounts to $n_{\text{vertex}} = 2(M-1)N + 1$ samples from the epistemic uncertainty space. Then, Latin Hypercube Sampling (LHS) [35] is employed to make $n_{\text{LHS}}$ additional samples in order to cover more of the epistemic uncertainty space within these hyper-rectangles. This is done since there is no guarantee in our case that the minimum and maximum of $Z(\boldsymbol{x})$ for each $\alpha$-cut can be found on the vertices of the corresponding hyper-rectangle. Latin Hypercube Sampling was chosen over random Monte Carlo sampling because of its space-filling properties and stability [35], which should make the methodology suitable also for higher-dimensional problems and extensive sensitivity analyses. Based on the samples $\boldsymbol{S_x}$, the function $Z(\boldsymbol{x})$ within the hyper-rectangle is approximated by a quadratic response surface (surrogate) model [36]

$$\widetilde{Z}(\boldsymbol{x}) = \beta_0 + \sum_i \beta_i x_i + \sum_i \beta_{i,i} x_i^2 + \sum_{i,k>i} \beta_{i,k} x_i x_k. \tag{11}$$

To solve Eq. (10), bounded quadratic optimization can then be applied to this function to find any maximum and minimum within the hyper-rectangle $\boldsymbol{A}_{\alpha_j}$, and the result is combined with the maximum and minimum of $Z(\boldsymbol{x})$ obtained by vertex optimisation [24]. This part of the uncertainty analysis methodology differs from that previously presented in [24] in the use of LHS and surrogate models, in addition to the presentation of outputs as possibility distributions.

## 3. Case study: accounting for the risk of HILP events in a grid investment decision

The development and testing of the methodology reported in this article has been carried out in parallel with a case study in collaboration with the Norwegian TSO Statnett. This case study concerns accounting for the risk of possible HILP events in the long-term system development plans for a region of Norway in addressing a specific and real grid investment decision problem. The details cannot be published due to confidentiality, but a simplified illustration of the transmission system in the region is shown in Fig. 2. Area 2 is a major load centre that expects a substantial but uncertain increase in load demand over the next decades. The problem involves two grid development alternatives (A and B) that are considered to ensure an acceptable level of security of supply in Area 2. Simply put, the difference between the alternatives as shown in Fig. 2 is that alternative B includes an additional transmission line into Area 2. This additional line is expected to reduce the likelihood of common-cause outages of the transmission lines between Area 1 and Area 2

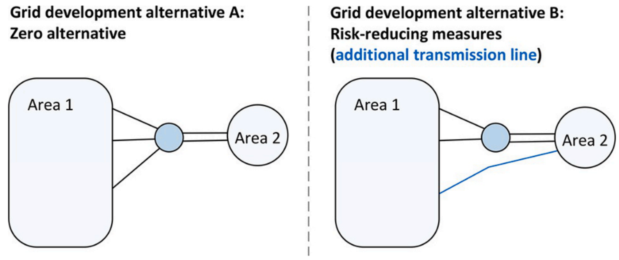


**Fig. 2.** System sketch for power system development case involving the choice between two grid development alternatives.

due to physical damage to the transmission infrastructure. Such an outage event is highly unlikely, but if it occurs it would result in long-lasting power supply interruptions in Area 2, and it is therefore regarded as a HILP event.

Grid development alternative A will be referred to as the *zero alternative*, which represents a continuation of the present grid situation. The zero alternative nevertheless needs to ensure compliance with laws and regulations and that the system can be operated in an acceptable manner, but it typically includes the minimal investment costs necessary to make it an acceptable alternative. In particular, the zero alternative in our case does not specifically include measures to reduce the risk of HILP events. This simple but concrete case allows us to focus on the key points of the uncertainty analysis methodology. The general methodology can also incorporate consequence analysis for more complex cases, but the illustration of the methodology for such cases would be less transparent. An implementation of the methodology for this case is available in MATLAB code [37] without the need of additional software tools.

### 3.1. Input parameters and characterization of uncertainties

Table 1 summarizes the assumptions made about the input parameters for the case. For all uncertain parameters in Table 1 except from $P_{\text{interr}}$ and $c$, no knowledge is available of any underlying stochastic processes. For these parameters a simplified expert elicitation scheme [38] was used to obtain estimates for parameter values and their uncertainty: TSO experts were asked to estimate the lowest and highest values they regarded as possible, considering the knowledge that was available. The uncertainty is characterized quantitatively in Table 1 by a lower limit $x_-$ and an upper limit $x_+$. The *best-guess* value $x_0$ for the parameter is the value they would use in an analysis where uncertainties are not accounted for explicitly. This value can also be interpreted as the most likely value. For instance, for the parameter $\lambda$, the uncertainty can be described by statements such as: "Our best guess is that such an event can be expected to occur once in 1000 years, but $\lambda$ could be as high as 1/(100 years) or as low as 1/(10 000 years)."

The "Uncertainty characterization" column in Table 1 summarizes whether uncertainties are a) primarily due to stochasticity (aleatory) or b) primarily due to lack of knowledge (epistemic). For the latter, the column also suggests the strength of knowledge associated with the uncertain parameter. For this case, one considers the strength of knowledge to be weakest for the frequency of occurrence $\lambda$. Such HILP events are expected to be extremely rare and correspond to unique situations [13,15], and there are no relevant existing statistics or experience base for similar events. The very large (epistemic) uncertainty estimated for $\lambda$ for this HILP event motivates the special attention it is given in this uncertainty analysis.

Possibility distributions are chosen to represent uncertainty in the parameters characterized in Table 1 as primarily associated with epistemic uncertainty. The input parameters defining the epistemic uncertainty space $\boldsymbol{A}$ are thus $\mathbf{x} = \{\lambda, f_{\text{red}}, f_P, f_c\}$ We furthermore define a triangular possibility distribution with $\pi(x) > 0$ for $x \in A_x$ and $\pi(x) = 1$ for the best-guess value $x = x_0$. This choice was made because we have a range of possible values and a value that is believed to be most likely but lack information justifying a more detailed uncertainty representation. Probabilistic uncertainty representations are chosen for those variables characterized in Section 3.1 as primarily associated with aleatory uncertainty. The variability in interrupted power $P_{\text{interr}}$ and specific interruption costs $c$ is modelled probabilistically using time series as described in Section 2.2. We use a time series $P(t)$ for the load demand in Area 2 with hourly measurements for six historic years. The specific interruption cost function $c(r, t)$ is in this case study given by the Norwegian CENS scheme [2–5], as described in the Appendix. Other interruption cost functions can be used in applying the methodology to other countries. Probability distributions are chosen to represent the uncertainty in the interruption duration $r$ and in the grid investment costs $C_{\text{A}}$ and $C_{\text{B}}$. Triangular probability density functions are considered to be reasonable approximations based on the TSO's experience.

The best-guess values for the relative annual load growth $f_P$ and the relative annual increase in specific interruption cost $f_c$ are based on prognoses typically used by the TSO in their long-term system development analyses for the area. The value of $f_c$ is an estimate of the annual increase in real income in the region, which is used by the TSO as an approximation for how much end-users value the reliability of supply. However, it is recognized that the knowledge basis underlying this parameter value is rather weak. We use an analysis horizon of $y_{\text{end}} = 40$

**Table 1**
Assumptions and uncertainty estimates for input parameters.

| Uncertain parameter, $x$ | Symbol and units | Best-guess value, $x_0$ | Uncertainty characterization for the case study | Lower limit, $x_-$ | Upper limit, $x_+$ |
|---|---|---|---|---|---|
| Frequency of occurrence (without risk-reducing measures) | $\lambda$ (per year) | 0.001 | Epistemic (unknown; fundamental lack of knowledge) | 0.0001 | 0.01 |
| Interrupted power | $P_{\text{interr}}$ (MW) | 250 | Aleatory (depends on the time of the power supply interruption; time series input data available) | n/a | n/a |
| Interruption duration | $r$ (hours) | 168 | Aleatory (primarily) | 84 | 504 |
| Specific interruption costs (given by Norwegian CENS scheme) | $c$ (NOK/MWh) | 55 000 | Aleatory if assuming the CENS scheme (depends on the time of the power supply interruption); epistemic contributions not considered here | n/a | n/a |
| Effectiveness of risk reduction measure (reduction factor for $\lambda$) | $f_{\text{red}}$ | 90% | Epistemic (medium strength of knowledge) | 50% | 100% |
| Annual load growth rate | $f_P$ | 0.87% | Epistemic (medium strength of knowledge) | 0.61% | 1.15% |
| Annual growth rate in specific interruption costs | $f_c$ | 1.3% | Epistemic (weak-to-medium strength of knowledge) | 0.0% | 2.0% |
| Grid investment costs (for zero alternative and for risk-reducing measures) | $C_{\text{A}}$ ($10^6$ NOK) | 950 | Aleatory (primarily) | 855 | 1045 |
| | $C_{\text{B}}$ ($10^6$ NOK) | 1150 | Aleatory (primarily) | 1035 | 1265 |

years and a discount rate $f_d = 4\%$. These parameters are not associated with uncertainty. For this case study it was assumed by the TSO that a certain HILP event can only occur once during the analysis horizon, since if it does occur, measures then would be implemented to avoid that it reoccurs.

### 3.2. Uncertainties in interruption costs due to HILP events

Fig. 3 shows the probability distribution (CDF) estimated for the case for the impact of a single HILP event. The impact is here measured by the interruption costs $IC_y = P_{interr,y} \cdot r \cdot c_y$, assuming that an event occurs in year $y = 1$. The cyan curve shows the effect of accounting for time-dependant correlations between load $P$ and specific interruption costs $c$. In other words, it captures the effect that load demand and the valuation of reliability of supply are both higher during winter months. The magenta curve is produced using the same marginal probability distribution for $c$ but neglecting time-dependant correlations. The expected value $\mathbb{E}(IC)$ is indicated by dashed lines, and the dotted line indicates the Value-at-Risk $VaR_{0.01}(IC)$. Accounting for time-dependant correlations clearly shifts the Value-at-Risk towards the right. This means that time-dependant correlations increase the contributions to the high-impact tail of the probability distribution and contribute to making extreme high-impact outcomes more likely. However, because time-dependant correlations also make relatively low-impact outcomes more likely, they do not appreciably shift the expected value.

Probability distributions for the interruption costs due to HILP events during the entire analysis horizon are shown in Fig. 4. For this case study, $N_{MC} = 10^5$ Monte Carlo realizations are used to estimate the CDFs. This gives a coefficient of variation below 2% for the estimated expected value, and we have verified that a higher value of $N_{MC}$ does not appreciably change the results presented below. We first consider $IC_A$, i.e. the present value of interruption costs due to HILP events for grid development alternative A (the zero alternative). The left-hand side of Fig. 4 shows the probability distribution $F(IC_A)$. The expected value $\mathbb{E}(IC_A) = 100 \cdot 10^6$ NOK is shown as a vertical dashed line. One immediately observes that the CDF rises abruptly from $F(IC_A = 0) = 0$ to $F(IC_A \gtrsim 0) \equiv 1 - p_{HILP,A} \approx 0.961$. The probability distribution for the interruption costs has this shape because the sampled interruption events are HILP events and thus assumed to be extremely rare. Most of the probability weight therefore lies at $IC_A = 0$, which is the outcome that no HILP events occur during the analysis horizon. The estimated probability of this outcome is more than 96%. If this probabilistic analysis had instead been applied to the case of more frequent (non-HILP) events, the CDF would have been increasing from $F(IC_A = 0) = 0$ with a smoother S-like shape.

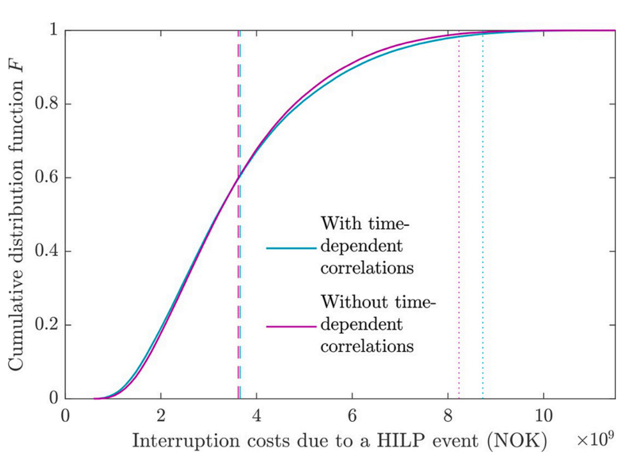


**Fig. 3.** Probability distribution for the interruption costs due to a single HILP event, assuming it occurs in year 1. Dashed and dotted vertical lines indicate expected values and $VaR_{0.01}$ values, respectively.

The probability distribution plotted for a narrower range of $F(IC_A)$ values and a wider range of $IC_A$ values is shown as an inset to better illustrate the distribution of the impact for the realizations where at least one HILP event does occur during the analysis horizon. When the distribution function is viewed on this scale, the expected value $\mathbb{E}(IC_A)$ lies very close to the $y$ axis and appears to be almost negligible compared to the potential high-impact outcomes in the tail of the distribution function.

The right-hand side of Fig. 4 shows how the risk of HILP events is changed if the risk-reducing measures are implemented (i.e. alternative B with an additional transmission line). Here, an alternative visualization is proposed where both the $x$ and $y$ axes are logarithmic to better show the full range of values for both IC and $F$(IC). This makes it easier to compare the CDFs $F(IC_B)$ and $F(IC_B)$ for the grid development alternatives. The intercept with the $y$ axis in Fig. 4 shows how the risk-reducing measures reduce the probability of HILP events from $p_{HILP,A} \approx 0.033$ to $p_{HILP,B} \approx 0.004$. Furthermore, the investment in an additional line reduces the expected value from $\mathbb{E}(IC_A) \approx 100 \cdot 10^6$ NOK to $\mathbb{E}(IC_B) \approx 10 \cdot 10^6$ NOK. These risk-reducing measures also affect the tail of the estimated probability distribution, and the dotted lines show how the Value-at-Risk $VaR_{0.001}(IC_A) = 6.5 \cdot 10^9$ NOK is reduced to $VaR_{0.001}(IC_B) = 3.4 \cdot 10^9$ NOK. These results quantify how the risk-reducing measures may lead to a substantial reduction in the risk associated with the most extreme (here: the worst 0.1%) outcomes, in addition to the reduction in the expected value. At the same time, the figure shows that there is still a possibility of very high-impact outcomes even with the additional grid investments of alternative B.

### 3.3. Uncertainties in socio-economic costs for grid development alternatives

We first consider a conventional cost-benefit analysis considering expected values where uncertainties are not accounted for explicitly. The results for the two grid development alternatives are shown in Figure 5. Here, the parameters $\mathbf{x}$ associated with epistemic uncertainties have been fixed to their best-guess value $\mathbf{x}_0$. These results will serve as a benchmark for the more comprehensive descriptions of risk presented later in this subsection, where the implications of both aleatory and epistemic uncertainties are explicitly accounted for and visualized.

Figure 5 shows that the expected total socio-economic costs $\mathbb{E}(TC(\mathbf{x}_0))$ are greater with an additional transmission line, with a best-guess estimate around $\mathbb{E}(TC_B(\mathbf{x}_0)) = 1150 \cdot 10^6$ NOK, compared to around $\mathbb{E}(TC_A(\mathbf{x}_0)) = 1050 \cdot 10^6$ NOK for the zero alternative. The additional transmission line is thus not cost-effective, which might imply that the TSO should choose the zero alternative. Since the figure shows expected values, the aleatory contributions to uncertainty are "averaged out" in this visual representation. In other words, these uncertainties are accounted for implicitly in the calculation of the expected values but not visualized explicitly.

We then consider the epistemic contributions to uncertainty by applying the probabilistic-possibilistic uncertainty analysis method to the case. The results are obtained using $M = 4$ $\alpha$-cuts and $n_{LHS} = 120$ additional samples of the epistemic uncertainty space. With $N_{MC} = 10^5$ as in Section 3.2, this gives a total number of $169 \cdot 10^5$ samples in the double-loop MC simulation. The number of samples was determined by increasing $n_{LHS}$ and $n_{MC}$ until there were no appreciable changes in the results as shown in the figures below.

Fig. 6 shows the possibility distributions $\pi(\mathbb{E}(TC_A))$ and $\pi(\mathbb{E}(TC_B))$ for the expected total socio-economic costs. Similarly as Fig. 5, this figure shows that the expected socio-economic costs $\mathbb{E}(TC)$ are most likely greater with an additional transmission line. However, Fig. 6 in addition illustrates how implementing the risk-reducing measures greatly decreases the uncertainty in the socio-economic costs. $\mathbb{E}(TC_A)$ could possibly become up to around $2050 \cdot 10^6$ NOK without risk-reducing measures, but these possibilities are eliminated with the

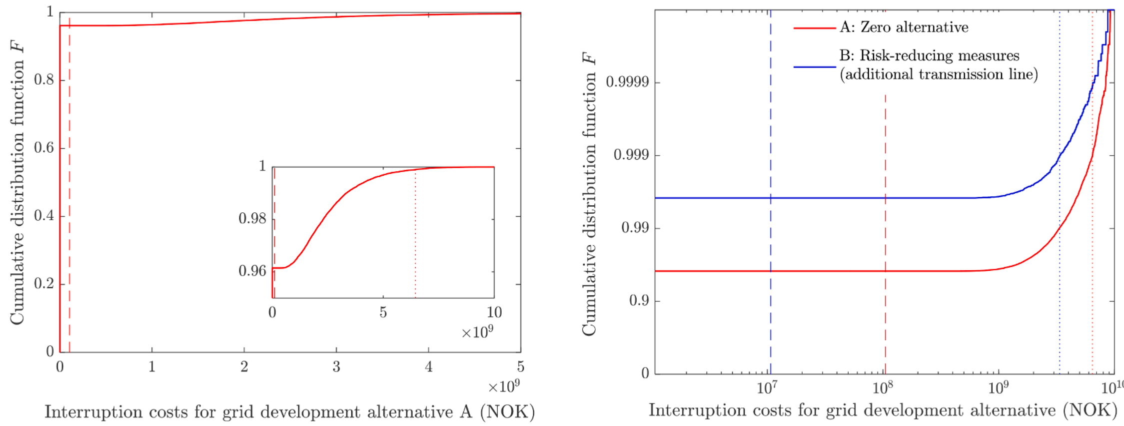


**Fig. 4.** Probability distribution for the present value of interruption costs due to HILP events over the analysis horizon for the zero alternative (left, and shown with alternative axis limits in the inset) and comparing the zero-alternative with the risk-reducing measure (right). Dashed and dotted vertical lines indicate expected values and $\mathrm{VaR}_{0.001}$ values, respectively.

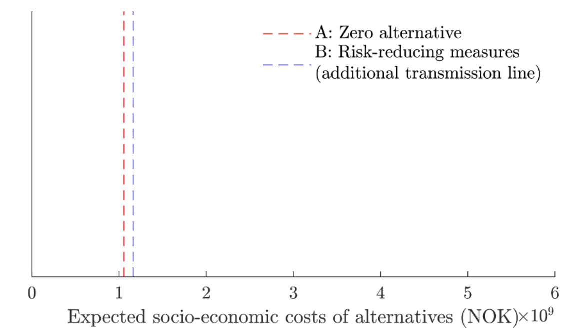


**Fig. 5.** Expected value of the total socio-economic costs for the two grid development alternatives.

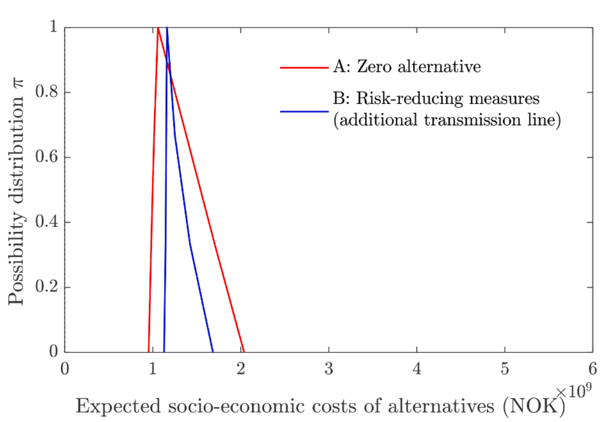


**Fig. 6.** Possibility distributions for the expected value of the total socio-economic costs for the two grid development alternatives.

investment of an additional transmission line.

Fig. 7 provides an explicit visualization of the contributions of both epistemic and aleatory uncertainties by comparing the probability bounds (p-boxes) for the total socio-economic costs TC for the grid development alternatives. Compared to Fig. 5 (showing only expected values) and Fig. 6 (showing only epistemic uncertainty contributions explicitly), Fig. 7 provides more information and a more comprehensive description of the uncertainties relevant to the grid development problem. (A similar visual representation has previously been proposed in the context of flood risk mitigation [27].) The probability bounds define the boundaries of CDFs for the variable that are possible given the

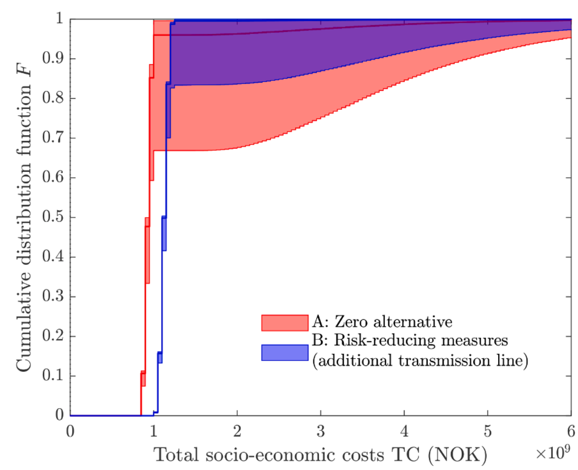


**Fig. 7.** Probability bounds (p-box) for the total socio-economic costs for the two grid development alternatives.

epistemic uncertainty contributions in the variable. Due to lack of knowledge one does not know the probability distribution function representing the aleatory uncertainty in TC, but one believes that its CDF has to be somewhere inside the coloured area of the p-box bounded by an upper and a lower CDF. The "best-guess" CDF for $\boldsymbol{x} = \boldsymbol{x}_0$ is shown inside the p-box with a thick unbroken curve. A purely probabilistic uncertainty analysis would only return information about this "best-guess" CDF.

The extent of the epistemic contributions to the uncertainty in TC can be appreciated from the width of the coloured areas of the p-boxes. The main contributor to this width is the uncertainty in the frequency $\lambda$. If this analysis had instead been applied to the case of a non-HILP event with much lower uncertainty in $\lambda$, the probability bounds around the "best-guess" CDF would have been much narrower. The additional value of this hybrid probabilistic-possibilistic methodology is therefore greater for HILP events with a substantial epistemic uncertainty in $\lambda$.

The width and the area for the risk-reducing measures (B) in Fig. 7 are much smaller than for the zero alternative (A). Similarly as for Fig. 6, this shows how investing in an additional transmission line reduces the epistemic uncertainties in the total socio-economic costs and constrains the aleatory uncertainties to be given by narrower bounds of possible CDFs. Comparing with Fig. 7, one realizes that the aleatory contributions to the uncertainty in TC are very large.

From Figure 5 it could be seen that the expected value of the total socio-economic costs was around $100 \cdot 10^6$ NOK higher for alternative B, with the risk-reducing measures involving an additional transmission line, than for the zero alternative. The best-guess estimate for the expected net benefits $\mathbb{E}(\Delta TC(\mathbf{x}_0))$ is therefore negative. According to this, investing in an additional transmission line is not socio-economic cost-effective. The probability bounds for the net socio-economic benefits $\Delta TC$ are shown in Fig. 8. Here, the best-guess expected value $\mathbb{E}(\Delta TC(\mathbf{x}_0)) \approx -100 \cdot 10^6$ NOK is indicated by a purple dashed line. Considering then the "best-guess" CDF (for $x = x_0$), shown as a thick unbroken curve, we can see from the intercept with $\Delta TC = 0$ that there is only a small probability that the benefits will outweigh the costs ("b>c"). This probability is estimated as $p_{b>c} = 1 - F(\Delta TC = 0) \approx 3.6\%$. However, considering all CDFs within the probability bounds that are possible, given our lack of knowledge, the probability that benefits outweigh costs may possibly be as high as $p_{b>c} = 1 - 0.67 = 33\%$ .

Although we do not include a detailed analysis of sensitivities in this article, we have checked what assumptions for uncertain parameters would make the expected net benefits $\Delta TC$ (the dashed line in Fig. 8) positive: A value of the frequency $\lambda$ of HILP events 2.2 times higher than the best-guess value $\lambda_0$ would make the investment in the additional transmission line cost-effective. This increased event frequency is still within the range of possible values $A_\lambda$. On the other hand, the investment cannot be made cost-effective by changing any other parameter $x$ with epistemic uncertainty within its range of possible values $A_x$. Developing methods for more advanced analysis of the sensitivity of the cost-benefit analysis to epistemic uncertainties and their interaction is proposed for future research.

## 4. Discussion

The methodology and results presented in the preceding sections have not presumed a specific risk attitude of the decision maker. Our starting point, however, as exemplified by the Norwegian Energy Act [6] in Section 1, was that the power system in principle should be developed in a socio-economic rational manner. This policy implies a risk neutral decision maker. Since the cost-benefit analysis in the previous sections resulted in a negative best-guess expected value $\mathbb{E}(\Delta TC(\mathbf{x}_0))$ for the net benefits, the conclusion would be that the TSO should *not* invest in an additional transmission line to reduce the risk of HILP events. On the other hand, if the decision maker allows some element of risk averseness, the methodology can be used to appraise the risk and the robustness of the conclusion more thoroughly. Appreciating the lack of knowledge, a risk averse decision maker could consider more conservative (or even worst-case) estimates of the uncertain parameters [19], which might imply that the TSO should invest in the additional transmission line after all. This illustrates how a more comprehensive description of risk may influence the grid development decisions that are made.

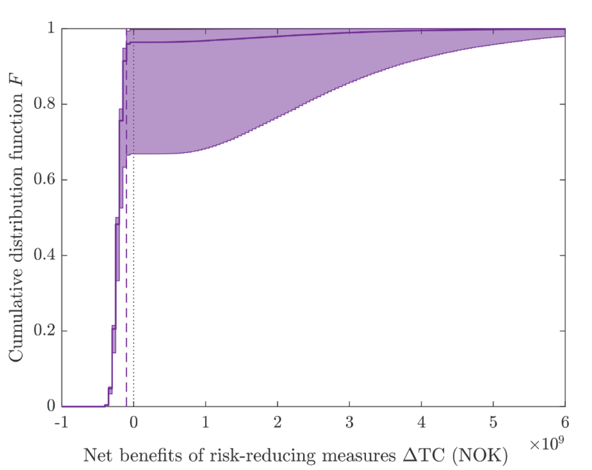


**Fig. 8.** Probability bounds (p-box) for net socio-economic benefits of risk-reducing measures. The best-guess CDF and expected value are shown with a thick unbroken curve and a dashed line, respectively.

However, for a TSO, risk management decisions should be viewed in a portfolio perspective: A grid investment decision problem as the case considered in this article is only one out of many decisions problems (i.e. grid investment projects) that the TSO considers at any given time. If the total costs of this portfolio of projects are large relative to the costs of a HILP event for an individual project, the TSO may be willing to accept this risk in order to minimize the expected socio-economic costs of the full portfolio, e.g. for an entire country. Let us for the sake of illustration assume that the TSO has 20 projects that are identical to the case considered above. Accounting for HILP events with a consistently risk-averse policy for all these projects implies a very substantial additional socio-economic cost due to grid investments of $4000 \cdot 10^6$ NOK. Assuming that the variables associated with aleatory uncertainty ($C_A$, $C_B$, $r$, $P_{interr}$, $c$) are uncorrelated across the projects, the expected net benefit of risk-reducing measures for all projects would be $-2000 \cdot 10^6$ NOK.

This example illustrates how one on could argue for a consistently risk neutral policy where each investment must be socio-economic rational. However, risk neutrality on a national level could mean that the TSO takes large risks on behalf of the population in some areas that is not shared by the rest of the population. In other words, distributional effects and considerations of fairness may have been neglected. Furthermore, one may have neglected systematic risks due to correlations between different projects and between the projects and the overall national economy. This can be relevant for parameters associated with epistemic uncertainty such as the increase in specific interruption costs $f_c$. Assuming a higher value of these parameters for one project likely means that one should also assume a higher value for the other projects in the portfolio.

Finally, in the face of great uncertainties in the likelihood of HILP events that render risk analysis difficult, an alternative and complementary vulnerability analysis approach can be considered [7]. Taking a vulnerability perspective means that one puts less emphasis on estimating the likelihood and more emphasis on understanding the potential consequences of HILP events, how they might arise, and how they can be mitigated. Such an approach may identify other and potentially less costly barriers against HILP events. If it is not cost effective with grid investment as a barrier to reduce the failure frequency $\lambda$, one may for instance consider barriers that reduce the interruption duration $r$ or emergency preparedness measures.

## 5. Conclusions

In this article, we have proposed a methodology accounting for uncertainties due to HILP events in socio-economic cost-benefit analyses. The methodology has been exemplified by a concrete case where a TSO considers investing in an additional transmission line to reduce the risk of HILP events. For this particular case, the expected net socio-economic benefits of these risk-reducing measures were negative ($-100 \cdot 10^6$ NOK). An additional transmission line is therefore not socio-economic cost-effective according to a conventional cost-benefit analysis only considering expected values and neglecting epistemic uncertainties.

However, we have demonstrated how the proposed methodology provides supplementary information describing the risk that can be balanced against the best-guess estimates of expected values provided by conventional cost-benefit analyses. More specifically, for the case study, the methodology could provide the TSO with the following additional insights:

- If a HILP event does occur, there is in this case a non-negligible chance that the impact in terms of interruption costs becomes higher than $9000 \cdot 10^6$ NOK (as quantified by $\mathrm{VaR}_{0.01}(\mathrm{IC})$). Such risk information would be hidden from the TSO if only expected values were presented.

- Time-dependant correlations between the underlying factors of the interruption cost contribute to making these extreme high-impact outcomes more likely. Specifically, both load demand and the valuation of reliability of supply (i.e. specific interruption costs) are higher during winter months in Norway.
- The socio-economic costs of each system development alternative have both epistemic and aleatory uncertainty contributions (as quantified and visualized by probability bounds), and the additional transmission line reduces the epistemic uncertainties significantly.
- Although an additional transmission line is most likely not socio-economic cost-effective, the probability that it will be cost-effective may possibly be as high as 33%.
- A value of the frequency $\lambda$ that is 2.2 times higher than the best-guess value would make the investment in the additional transmission line cost-effective for this case. Changes in the other parameters with epistemic uncertainties, on the other hand, would not be enough to make the investment cost-effective.

Such quantitative results and insights could not have been obtained using previously published qualitative methodologies for describing uncertainties due to HILP events [14]. Previously published quantitative methodologies [18,24–27], although based on methods related to those we employ, could not have provided comparable results since they were not adapted to power system development problems.

The consequence and causal analysis parts [7,14] of the risk assessment considered in the case study have been deliberately kept relatively simple and transparent. For the simple topology of the transmission system in this case, more detailed consequence analysis would be of little value since the other contributions to the uncertainties in the risk assessment are so large. The general uncertainty analysis methodology proposed in this article is however applicable also to more complex transmission system cases. For such cases and for applications to sensitivity analysis, further work could investigate how the accuracy and computation time would scale as the dimensionality of the uncertainty space increase. Other extensions of the methodology may require more careful consideration and further research, such as more accurate valuation of reliability of supply and aspects of the societal costs of HILP events beyond those currently captured in CENS schemes [39]. Interruption cost estimates according to CENS schemes can be considered as lower bounds for the total socio-economic costs of the power interruption [28], and other aspects of the societal costs of HILP events are all associated with additional uncertainties.

## CRediT authorship contribution statement

**Iver Bakken Sperstad:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing - original draft. **Gerd Kjølle:** Conceptualization, Funding acquisition, Supervision, Writing - review & editing. **Eivind Ødegaard Norum:** Conceptualization, Investigation, Writing - review & editing.

**Table 2**
Sector customer damage functions measured in NOK/kW (cost level 2018) at the reference time, with interruption durations $r$ measured in hours, valid for $r > 72$ hours.

| Customer sector | Customer damage function |
|---|---|
| 1: Commercial | $149.12 \cdot r$ |
| 2: Industry | $65.37 \cdot r$ |
| 3: Residential | $13.36 \cdot r + 209.61$ |
| 4: Agriculture | $19.63 \cdot r$ |
| 5: Public | $41.64 \cdot r$ |
| 6: Energy-intensive industry | $3.232 \cdot r + 105.05$ |

**Table 3**
Composition of customer types for end-users at risk of power interruptions in the case study, given by the fraction of the average load demand in the region.

| Energy-intensive industry | Agriculture | Industry | Public | Commercial | Residential |
|---|---|---|---|---|---|
| 2% | 4% | 11% | 14% | 28% | 41% |

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix

In the case study, the specific interruption cost is calculated based on the Norwegian CENS scheme [2–5]. However, some adjustments and simplifications appropriate for HILP events with extraordinarily long interruption durations are made as described below. The specific interruption cost $c$ for a power supply interruption event is calculated as [17,34]

$$c(t,r) = \sum_{i=1}^{6} c_{\mathrm{ref},i}(r) \cdot f_{\mathrm{corr},i}(t) \cdot P_{\mathrm{ref},i} \bigg/ \overline{P}. \tag{12}$$

Here, the sum goes over all customer types $i$ defined in the scheme, $c_{\mathrm{ref},i}(r)$ is the sector customer damage functions for the reference time (“a workday in January”), $f_{\mathrm{corr},i}(t)$ are time-dependant correction factors, $P_{\mathrm{ref},i}$ is the load at the reference time, and $\overline{P}$ is the average load as calculated from the entire input load time series $P(t)$.

Table 2 specifies the sector customer damage functions $c_{\mathrm{ref},i}(r)$ used for the case study. Statnett’s own cost functions (for duration $r > 24$ hours) are used for all customer types except 3 and 6; for residential customers (type 3), survey results reported in [39] for extraordinarily long interruptions (duration $r > 72$ hours) are used; for energy-intensive industry (type 6), the ordinary CENS scheme customer damage function [2] for $r > 8$ are used. The composition of customer types for the area considered in the case study is specified in Table 3.

The interruption duration for the HILP events that are considered is much larger than the time scales characterizing variations in load and specific interruption costs within a day or within a week. For simplicity, we therefore only consider the time-dependant correction factors $f_{\mathrm{corr},i}(t)$ averaged over each month. This approach is sufficient to capture the seasonal time-dependant correlations between load and specific interruption costs, e.g. the effect that load demand and the valuation of security of supply are both higher during winter.

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