Safety and Reliability – Safe Societies in a Changing World – Haugen et al. (Eds)

Development of a qualitative framework for analysing high-impact low-probability events in power systems

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ABSTRACT: High-Impact Low-Probability (HILP) events in power systems historically involve a multitude of aspects, including diverse and disparate threats, failures and sequences of events. Each of these aspects are associated with different types of uncertainties. In practice, the analyst has to make trade-offs between computational efficiency and accuracy in the different aspects that are included in the analysis. Without a clear understanding of the specific problem to be solved and which aspects that are important to capture, elaborate quantitative analysis may be of limited value. This paper presents the development of a *qualitative* framework for analysing HILP events in power systems. By mapping aspects of power system HILP events to a bow-tie model, it provides a framework for defining, decomposing and delimitating decision problems related to such events. The framework may guide the analyst in the development and application of methods for quantitative analysis and for considering different types of uncertainties.

1 INTRODUCTION

A High-Impact Low-Probability (HILP) event, also referred to as an extraordinary event, is an event with a high societal impact and a low probability to occur. In power systems, such events are often understood as blackouts, i.e. wide-area power interruptions. A number of such major blackout events have occurred in the last few decades (Bompard et al. 2013, Hillberg 2016), each resulting in critical consequences to society. Such events therefore receive great attention both by power system operators and other stakeholders, such as researchers and the general public, despite their low probability of occurrence. Partly due to this low probability, these events typically are not captured in conventional reliability and risk analyses, which calls for analysis approaches specific to HILP events.

HILP events historically involve a multitude of diverse and disparate threats and complex sequences of events, which present the analysts and researchers studying them with numerous uncertainties. Relevant aspects that can be taken into account in quantitative modelling of HILP events include: failure bunching due extreme weather (Panteli and Mancarella 2015), other natural hazards, cascading outages (Vaiman et al. 2012, Dobson and Newman 2017), dynamic phenomena, system protection schemes (Hillberg et al. 2012), corrective actions (Vadlamudi et al. 2016), and valuation of the societal impact. Different approaches and methodologies exist for quantitatively analysing these events (Gjerde et al. 2011), including methods of identifying unwanted events, causal analysis, consequence analysis, and risk and vulnerability evaluation. Such methods typically focus on one or a subset of all potentially relevant aspects. The realization is that there is no single methodology covering all these aspects that is suitable for analyzing HILP events in power systems (Kjølle et al. 2013), and the full set of aspects is too comprehensive to analyse quantitatively. Without a clear understanding of what specifically is the problem to be solved or decision to be supported, and consequently which aspects are important to capture, elaborate quantitative analysis may be of limited value.

In this paper, we take a broader view on HILP events and present the development of a qualitative framework for analysing HILP events in power systems. A qualitative framework provides the analyst with a more complete overview of the set of problems and a starting point for detailed analysis. Previous work on HILP events largely focus on methods of detailed, quantitative analysis (Vaiman et al. 2012), but some work on the more conceptual level also exists. For instance, (Watson et al. 2014) developed a framework for resilience metrics for energy infrastructures. In (Veeramany et al. 2016), an overarching modelling framework is formulated under which different models can be integrated for an multi-hazard risk assessment of power system HILP events. The cascading aspect of some HILP events is discussed conceptually in (Vaiman et al. 2012, Dobson and Newman 2017).

The qualitative framework presented in this paper is based on an existing framework for power system vulnerability analysis (Kjølle et al. 2013, Kjølle and Gjerde 2015). The present paper advance previous work and attempts to consolidate relevant aspects of HILP events in a consistent and all-encompassing mapping. This framework explicitly discusses and structures uncertainties related to different decision problems. The framework is presented in Section 2, which forms the bulk of this paper. Subsection 2.1 shows how mapping relevant aspects and their relationships to a bow tie model provides a more complete overview of HILP events. Subsection 2.2 to Subsection 2.4 presents an approach to defining, delimitating and decomposing decision problems related to HILP events. This provides a starting point for quantitative analysis, as discussed in Section 2.4, and a basis for taking into account uncertainties, which is discussed in Section 2.5. Throughout these subsections, concrete examples of problems are discussed to illustrate the application of the framework. Finally, Subsection 3 concludes the paper and indicates future work in refining and applying the framework.

2 QUALITATIVE FRAMEWORK FOR HILP EVENTS

The qualitative framework presented in this paper is based on the conceptual bow tie model and a previously developed framework for power system vulnerability analysis (Kjølle et al. 2013, Kjølle and Gjerde 2015). The bow tie model describes the relationship between causes and consequences of unwanted events, which are here defined as power system failures. Note that the unwanted event in the centre of the bow-tie is not by itself a HILP event, but it could be the initiating event of a sequence of events with critical consequences that constitutes the HILP event.

2.1 *Getting a better overview of relevant aspects*

The bow tie model can be used as a visual aid in structuring the causes and consequences of unwanted events as illustrated in Figure 1. This figure gives a comprehensive overview of aspects relevant to HILP events in power systems and how these relate to each other. Such an overview is useful when structuring an analysis of HILP events.

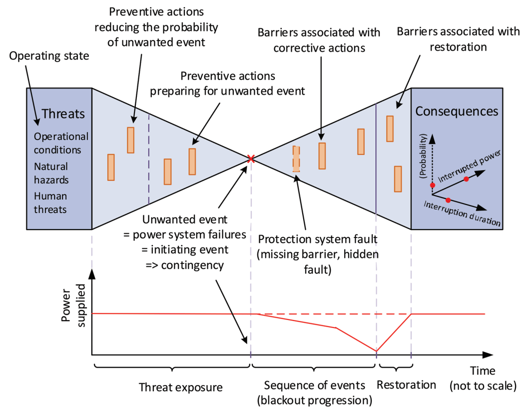

Figure 1. Overview of relevant aspects of HILP events in power systems mapped to a bow-tie model.

The left-hand part of the figure shows schematically how the exposure of the power system to different threats can cause power system failures, and the right-hand part shows how power system failures can result in consequences external to the power system, i.e. societal impact. The criticality of the consequences can be measured along different dimensions, but for the illustrations in this paper we will consider total end-user power interruption (MW) and interruption duration (hours) as the two principal dimensions. Each HILP event could, in principle, also be associated with a probability. Other relevant factors include the types of end-users affected and the dependence of the society on electricity supply; for further discussion of the definition of "critical", we refer to (Kjølle et al. 2013, Kjølle and Gjerde 2015).

Relevant threats on the left-hand side include conditions related to the operating state of the power system (e.g. challenges related to the power import/export situation, prior outages, etc.), natural hazards such as major storms and human threats. Barriers on the left-hand side of the bow tie reduce the susceptibility of the power system to threats. These barriers reduce the probability of unwanted events through preventive actions such as condition monitoring, preventive maintenance and vegetation management. Some barriers also preemptively increase the coping capacity of the system to reduce the probability of critical consequences in case an unwanted event does occur. This category of barriers includes preventive scheduling, grid reconfiguration and islanding in preparation for a major storm.

Barriers on the right-hand side of the bow-tie are intended to reduce the consequence of power system failures and correspond to the coping capacity of the power system with respect to these unwanted events. Examples of such barriers are corrective actions such as emergency generation rescheduling, controlled load shedding, controlled islanding, and various system protection schemes. Other barriers are associated with the restoration of system operation after power has been interrupted, for instance the black-start capability of generators and the availability of spare parts, equipment and competent personnel.

To illustrate the distinction between these two types of barriers, we have in Figure 1 superimposed a timeline with an example of how the interrupted power could develop as a function of time throughout the course of the HILP event. The sequence of events after the occurrence of the initiating event can be broadly separated in a blackout progression phase and a restoration phase. Corrective action barriers are associated with the blackout progression phase and primarily intended to reduce the amount of interrupted power, whereas barriers associated with the restoration phase generally intended to reduce the restoration time and thus the interruption duration.

2.2 *Defining and framing the problem*

The analysis of HILP events in power systems is a broad problem area involving different decision problems as well as more fundamental research problems. The question one needs to ask is why one is interested in analyzing HILP events the first place. It is necessary with a clear definition the problem and a clear understanding of the motivation and purpose of solving the problem.

Figure 2 shows two dimensions that can be used to frame problems related to HILP events: The time scales for power system-related decisions and relevant stakeholders or decision makers. The figure

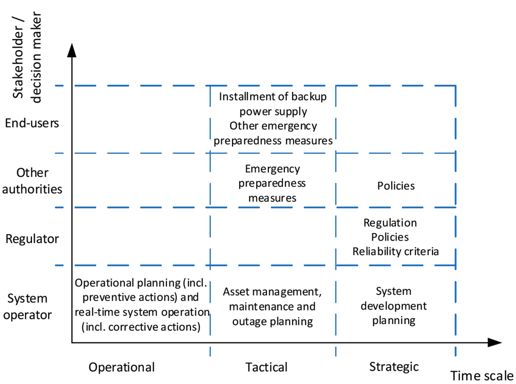

Figure 2. Two dimensions relevant for framing problems related to HILP events: The stakeholder or decision maker, and the time scale of relevant decision problems.

also indicates the motivation of the stakeholders with regards to HILP events. The two dimensions in Figure 2 determine what information is available to the analyst and thus what uncertainties must be taken into account. This will be discussed in more detail in Section 2.5.

Here we will distinguish between operational, tactical and strategic decisions by the time scale of the planning horizon that is considered. Following the classification in (GARPUR Consortium 2016), these three time scales correspond to system operation (including both real-time operation and day-ahead operational planning), asset management, and system development or planning, respectively. Note that other references may use other terms and definitions for the time scales. For instance, (Watson *et al.* 2014) distinguishes between system planning decisions and policy decisions, and (Yang and Haugen 2015) defines both strategic and operational decisions as planning decision, which are in turn distinguished from instantaneous or emergency decisions.

Stakeholders can be differentiated in terms of their influence over power system related decisions, and since system operators have the most direct influence, we will in the following take the perspective of the system operator as a decision maker. Furthermore, we will focus on transmission system operators (TSOs) since distribution system operators (DSOs) have less influence over decisions relevant for wide-area power interruptions. In practice, decisions will be taken by different departments and at different levels in the organisation, but in the following we simply refer to the decision maker as "the system operator".

To put the more general problem of analysing HILP events in a decision-making context, Figure 3 shows some examples of relevant decision problems for system operators, sorted by time scale. These decision problems will be defined in broad terms below and be used in the following sections to illustrate the qualitative framework. Although we do not define the decision problems formally in terms of their objective function etc. as done e.g. in (GARPUR Consortium 2016), it

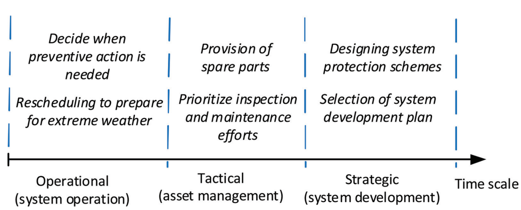

Figure 3. Examples of decision problems for transmission system operators with relevance for the analysis of HILP events.

is important to keep in mind that these reliability management decisions typically involve some form of trade-off between costs and reliability of supply. The value of reliability of supply is sometimes monetized in the form of expected interruption costs, i.e. the cost of energy not supplied.

Selection of system development plan: An example of a strategic decision problem is the evaluation of candidate system development plans (e.g. for new transmission lines) and selection of the best candidate. Regulation may dictate that a socio-economic cost-benefit analysis of the candidates is performed. Ideally, the cost of energy not supplied associated with possible HILP events should be included in such an analysis.

Designing system protection schemes: System protection schemes (SPSs) are important examples of barriers on the right-hand side of the bow-tie, and the system operator has to plan which SPSs to implement. The motivation of implementing an SPS could be to increase the transmission capacity of the system as well as to increase the coping capacity of the system with respect to the occurrence of contingencies that would otherwise result in critical consequences (Hillberg *et al.* 2012).

Prioritize inspection and maintenance efforts: The system operator has to decide how to best allocate limited resources for preventive actions such as intensified inspection and maintenance and improved condition monitoring of power system components. Mitigating certain susceptibilities could help reduce the risk of HILP events as well as more ordinary events.

Spare parts etc. for critical components: If the power system is vulnerable to the loss of certain component, e.g. a transformer, the decision can be made to provide for spare parts to reduce the duration of potential power interruptions.

Decide when preventive action is needed: During operation, preventive actions such as generation rescheduling may be needed e.g. due to the development of threat exposure and/or the operating state. The first step for the system operator is to correctly assess the situation and decide whether or not to effectuate preventive actions.

Rescheduling generation e.g. to prepare for extreme weather: During an extreme weather event the near-simultaneous failure of multiple transmission lines (failure bunching) is more likely. In this case, one relevant preventive action is to reschedule generation in a way that makes the power system better able to cope with failures on one or several transmission lines.

2.3 *Defining and delimiting the analysis*

Decision making for problems as exemplified above can be supported by the analysis of HILP events. One way of defining and delimitating "analysis of HILP events" is to consider sub-problems distinguished by the objective of the analysis. One possible classification is:

1. identifying critical contingencies
2. identifying critical operating states
3. identifying critical barriers
4. assessing the contributions to the overall reliability of supply

Each of these sub-problems can be associated with different parts of the bow-tie model as illustrated in Figure 4. In practice, the objectives may be overlapping and the sub-problems may be combined in one of the same analysis. The classification may nevertheless be useful in discussing specific decision problems and the underlying motivation.

2.3.1 *Identify critical contingencies*

A critical contingency is here understood as a failure or unplanned outage of a power system component that may potentially result in critical consequences. One purpose of identifying critical contingencies is to identify critical power system components with the motivation to strengthen or introduce appropriate barriers, cf. Section 2.3.3.

One example of a system operation decision involving the identification of critical contingencies is the (optimal) preventive rescheduling of generation in preparation for an extreme weather event. In this case, the system operator should ideally know which (critical) higher-order contingencies to take into account when rescheduling. In the context of system development, one would like to identify critical contingencies in the candidate development plans to reduce the vulnerabilities of the development plan that is selected. Another purpose of identifying critical contingencies can be to screen contingencies to be considered as input to more detailed (e.g. dynamic) analysis.

2.3.2 *Identify critical operating states*

We here understand a critical operating state as an operating state which in combination with a

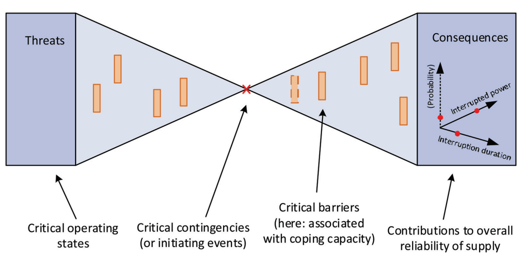

Figure 4. The placement in the bow tie model of different criticalities and sub-problems relevant in the analysis of HILP events.

critical contingency potentially result in critical consequences. The motivation for identifying these could be to increase the situational awareness of the system operators, which has previously been identified as being crucial to avoid HILP events (Johansson, E. *et al.* 2010). Situational awareness is relevant for operational decisions on which corrective actions to carry out after a contingency has occurred. Identifying critical operating states prior to contingencies may also be important to be able to decide when preventive action is needed.

2.3.3 *Identify critical barriers*

The identification of critical barriers may be used in selecting barriers to strengthen, and the identification of critical barriers that are missing may be used in proposing new barriers to put in place. This involves corrective barriers such as well-designed system protection schemes, or preventive barriers such as inspection and maintenance. For the latter example, the decision of which components to prioritize also depends on the identification of critical contingencies.

2.3.4 *Assessing the contributions to the overall reliability of supply*

An underlying premise of this work is that conventional power system reliability analysis methods do not fully capture HILP events. The reliability of a power system can be defined as "the probability of its satisfactory operation over the long run. It denotes the ability to supply adequate electric service on a nearly continuous basis, with few interruptions over an extended time period" (Kundur *et al.* 2004). The overall reliability of supply may be quantified by reliability indices such as the expected annual energy not supplied. Over the long run, HILP events do contribute to these reliability indices, but their contribution may be underestimated by conventional reliability analysis methods. For instance, this may happen when the methods do not capture failure bunching, protection system failures, or any of the other aspects and dependencies that may conspire to result in a HILP event. Furthermore, the short-term impact of a HILP event may be disproportional to their long-run visibility in expected values of reliability indices and therefore warrant separate treatment (Vaiman *et al.* 2012). These are some of the reasons why methods of vulnerability analysis focusing on HILP events have been advocated to complement traditional risk and reliability analysis methods (Johansson *et al.* 2013, Kjølle and Gjerde 2015).

Nevertheless, estimates of reliability indices are used by system operators as part of their reliability management processes also for decisions relating to HILP events. An example is the selection of system development plans for a given region, supported by a socio-economic cost-benefit analysis including expected interruption costs. If the region is exposed to strong winds, this could motivate capturing the contribution of HILP events due to failure bunching effects in the estimated interruption costs.

2.4 *Decomposition in quantitative analysis*

After defining the purpose of the analysis, one needs to consider which quantities the analysis method needs to estimate and which of them is most important to estimate accurately. Here we will consider three primary output parameters: 1) The probability of an event and its consequence in terms of 2) power interrupted and 3) interruption duration. As illustrated in Figure 5, these output parameters are broadly speaking associated with different parts of the bow-tie model. To assess the consequences of an unwanted event, it is sufficient to consider the right-hand side of the bow-tie: The interrupted power is primarily determined by the sequence of events within the phase labelled "blackout progression", and the interruption duration is primarily determined by the events in the restoration phase. On the other hand, to determine the probability of a HILP event, characterized by a given consequence, one has to consider both the left-hand side (with the label "threat exposure" in Figure 5) and the right-hand side of the bow-tie.

To approach more quantitative analysis and consideration of different uncertainties, we overlay the bow tie model with a schematic data flow diagram for the analysis in Figure 6. A cause analysis is depicted on the left-hand side of the bow tie that gives as output the failure rate (or the probability of failure during a certain time interval) for a given unwanted event (i.e. a given power system failure). Such a module could for instance be based on a fault tree. Failure bunching effects, for example due to major storms, could be incorporated in this step using existing tools for estimation of wind-dependent failure rates, as done in (Solheim *et al.* 2016).

The consequence analysis on the right-hand side of Figure 6 is divided in two modules representing

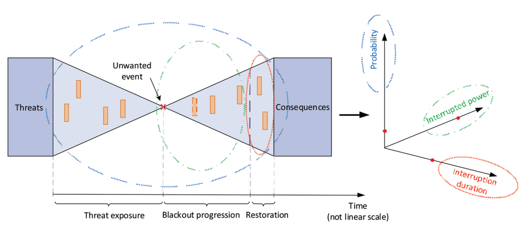

Figure 5. Illustration of how the problem of analysing extraordinary events can be decomposed and delimitated based on what quantity one is focusing on estimating.

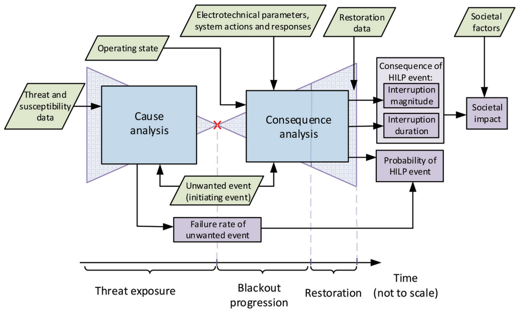

Figure 6. Schematic of quantitative analysis (blue, within the bow-tie) with input data (green parallelograms) and output data (purple).

the blackout progression phase and the restoration phase, respectively. The module for the blackout progression phase models system responses and resulting power interruptions. It could be based on an event tree model, power flow analysis, dynamic analysis, etc. This module can take as input electrotechnical parameters describing the power system and its operational limits as well as parameters describing the actions and responses in the system. For instance, if the analysis method is based on an event tree accounting for corrective action failures (Vadlamudi *et al.* 2016), input parameters can be conditional probabilities determining the probability of different sequences of events. The restoration phase module represents the restoration process. For instance, the restoration time could be modelled by average outage times of the components involved, in which case such outage times are needed as input. Alternatively, the restoration process could be modelled in more detail, which would require additional input parameters.

When analyzing system protection schemes to identify critical barriers for certain unwanted events, it may not be important for the purpose of the analysis to consider what caused these unwanted events. For such an analysis, one could omit the left-hand side of Figure 6 and focus on the first part of the consequence analysis, e.g. using dynamic analysis to estimate the power interrupted. On the other hand, if the objective is to assess the contribution to the overall reliability of supply, one would typically also have to represent power system restoration in the analysis.

In the determination of the consequences illustrated in Figure 6, the consequence analysis stops after finding the interruption magnitude and duration. However, as mentioned in Section 2.1, the societal impact of an HILP event is not determined by these two parameters alone. The box labeled societal factors in Figure 6 represent other factors determining the societal impact, such as the type of customers (end-users) and the criticality of the loads that are interrupted. Consequences of power interruptions are typically monetized using interruption cost functions determined by customer surveys, but these interruption costs give only a lower bound for the total socio-economic costs of the power interruption (GARPUR Consortium, 2016). Estimating quantitatively the impact on society more widely might involve modelling of the interactions between the power system and other infrastructures (Johansson et al. 2015).

2.5 *Taking into account uncertainties*

HILP events can be argued to be inherently associated with uncertainties (Taleb 2010, p. xxviii). Factors such as the operating state, the technical condition of components and failure bunching effects due to adverse weather all have their own individual uncertainties. HILP events are often the results of multiple, interacting factors and circumstances. As such, their combined uncertainty is larger than the uncertainty of the individual factors.

First, it is common to classify uncertainties as either aleatory, i.e. associated with random variability, or epistemic, i.e. associated with a lack of knowledge. Given that HILP events are characterized by a scarce experience base and severe lack of knowledge, epistemic uncertainties are especially important to consider. Next, following a similar classification as in (Rausand 2013), we will broadly distinguish between three types of uncertainties:

- Input data uncertainties
- Modelling uncertainties
- Completeness uncertainties

For the analysis of HILP events in power systems, these types of uncertainties can be related to Figure 6 as follows. Input data uncertainties and modelling uncertainties are related to green and blue boxes, respectively. The additional category that we have here chosen to label “completeness uncertainty” represents uncertainty associated with the completeness of the models of the system. Although there are different ways to understand this term (Rausand 2013, Aven 2016), and “completeness uncertainty” may not be unambiguously distinguished from “modelling uncertainty”, we find the term useful to describe uncertainty associated with aspects omitted and/or outside the scope of the analysis. As an example, a consequence analysis starting from a given set of contingencies (i.e. covering only the right-hand side of Figure 6) does not explicitly consider what might have caused the contingencies. If the problem was to identify effective system protection schemes, for instance, threat and susceptibility aspects may not have been within the scope of the analysis.

Sources of incompleteness in the analysis can be either known or unknown to the analyst (Aven 2016). If the analyst is unaware that an aspect is not considered in the analysis, this uncertainty can be labelled an "unknown unknown" (Feduzi and Runde 2014). Here, we use this term in a wider sense to refer to lack of knowledge that is implicit, i.e. a form of epistemic uncertainty associated with "what we don't know we don't know". Furthermore, we focus on "unknown unknowns" that are "knowable", i.e. that can in principle be transformed into "known unknowns" (Feduzi and Runde 2014).

Another way to classify uncertainties related to an analysis of HILP events that is more specific to the domain of power systems is to consider uncertainties related to the aspects discussed in Section 2.1. An example of such a classification is illustrated in Figure 7. Here, each of the categories along the vertical axis corresponds to one of the components of quantitative analysis that were illustrated in Figure 6. This shows how a domain-specific classification can be combined with the generic uncertainty classification discussed above: For each category, a given analysis is associated with uncertainty (indicated along the horizontal axis) related to the accuracy of modelling assumptions and the input data.

This multi-dimensional classification of uncertainties can be used to structure a qualitative assessment of the strength of background knowledge (Aven *et al.* 2014, p. 87) underlying a given analysis: If an aspect is modelled in a simplified or inaccurate manner, the knowledge of this aspect that is represented in the analysis is weak and the uncertainty is correspondingly high. Even if the modelling of an aspect is accurate, the uncertainty is still high if the associated input data represented in the analysis is inaccurate.

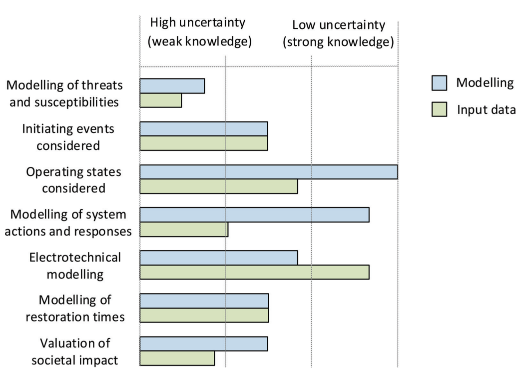

Figure 7. Example of classification and assessment of uncertainties associated with analyses of HILP events.

Such a structured assessment of the uncertainties of a HILP event analysis can be used by the analyst to rank which uncertainties are most important (Aven *et al.* 2014) to improve the overall accuracy and suitability of the analysis. More accurate modelling of an aspect often implies longer computation times. In practice, a trade-off must therefore be made between computational efficiency and accuracy, and trade-offs must be made between the modelling accuracy for the different aspects considered in the analysis.

An explicit qualitative assessment of uncertainties can also be used as a basis for comparing different analyses and informing the decision maker of their uncertainties (Aven *et al.* 2014). As an example, one can consider methods designed to analyse cascading outages. A number of such methods have been developed, each focusing on different subsets of the mechanisms and aspects involved in cascading outages. Considerable efforts have already been devoted to reviewing and validating such methods (Vaiman *et al.* 2012, Bialek *et al.* 2016), but there are still many open questions that may limit their credibility in decision making. More explicit classification and assessment of their uncertainties, scope and purpose could help inform system operators of which methods are most suitable for different problems.

Completeness uncertainty is not included as a separate dimension in Figure 7, but if an aspect is not covered in an analysis, the modelling uncertainties related to this aspect can be regarded as high. However, to fully characterize the completeness uncertainty dimension of the analysis one needs to identify and uncover "unknown unknowns". It has been argued that to do so, the analysis needs to be placed in a sufficiently broad framework and avoid starting out with a too narrow view of the problem (Feduzi and Runde 2014, Aven 2016). A qualitative mapping of relevant aspects to the analysis as proposed in this paper can contribute to transforming "unknown unknowns" to "known unknowns", or in other words making implicit assumptions and uncertainties explicit. Communicating such uncertainties associated with the completeness of the analysis can change, from the perspective of the decision maker, a "unknown unknown" to a "known unknown". To give a simple example: When deciding on system protection schemes to mitigate cascading outages and the analysis does not model the dynamics of rotor angle stability, the decision maker should be aware that the type of cascading events characterized by generators losing synchronism is omitted from the analysis.

As mentioned in Section 2.2, the time scale of the decision problem is relevant for what information is available during the analysis and hence what is uncertain and what is known. For instance, the system operator knows the operating state to a good approximation during real-time system operation, whereas this information is not available for an analysis for long-term planning purposes (Vaiman et al. 2012). For the example of cost-benefit analysis including the contributions of wind-related failures, the analyst needs to assume a selection of operating states expected to be representative of the future, and this is associated with additional uncertainties. For the example of preventive rescheduling in preparation of a major storm, more information is available on the operating state over the planning horizon, although this is still imperfect information as one may have to consider the forecast uncertainties.

3 CONCLUSIONS AND FUTURE WORK

This paper proposes a qualitative framework for analysing HILP events in power systems that may complement or guide more quantitative analysis. Mapping relevant aspects of such HILP events to a bow tie model provides the analyst with a broad overview of the set of problems at hand and a starting point for detailed analysis. Although the full set of aspects is too comprehensive to analyse quantitatively, the qualitative framework provides a basis for decomposing and delimitating the problem: Defining precisely the purpose of the analysis, one can then choose what aspects need to be modelled accurately and which aspects one is choosing to omit. Omitting and neglecting aspects of the overall problem introduce uncertainties in the analysis, but by being explicit about what is omitted and assumed one reduces the amount of "unknown unknowns" in the analysis and may thus support more well-informed decisions.

Further work will test the applicability of the framework in case studies of real problems related to HILP events. The approach for defining the purpose of an analysis and delimitating the problem presented will also be used to guide the development and application of methods for quantitative analysis of HILP events. Furthermore, the classification of models and input data for the analysis may form the basis for considering which methods are most appropriate for handling different types of uncertainties related to modelling choices and input data.

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