Identification, visualization and reduction of risk related to HILP events in power systems

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***Abstract*—High Impact Low Probability (HILP) events in the power system can have severe consequences for society. The concept of power system resilience has recently been applied to study such events. The paper discusses the definition of a HILP event and proposes a complimentary approach to studying power system resilience. This approach considers the probability of a scenario occurring and the subsequent consequences. The article further proposes methods to identify, communicate and subsequently reduce the probability of such events happening. The applicability of the methods is exemplified through a case study using the Roy Billinton Test System (RBTS) and 25 years of historical weather data. The results show that the method can be used to illustrate high-risk HILP events to support operational resilience planning, and how a developed resilience contribution measure can be used to prioritize grid hardening efforts.**

***Index Terms*-- extreme weather, reliability, resilience, HILP, extraordinary events, visualization, correlation, hardening.**

I. Introduction

Power system outages can have severe consequences as society is dependent on a steady supply of electricity. High Impact Low Probability (HILP) events are rare events with large consequences, and the identification of scenarios leading to such consequences is of great importance. One of the main causes of major blackouts has been shown to be severe weather events [1]–[3]. Using historical weather data can give additional insights into weather patterns that may cause HILP events to occur. While historical weather patterns will not directly predict an extreme event which has never occurred, it will none the less give some insight into the historical risks of an event. A HILP event may be more extreme than previously identified risks but knowing the historical risk can still contribute to reduce the probability of future events, assuming similar patterns of threat exposure.

Once potential HILP events are identified, they must be communicated to relevant stakeholders. Visualization of risks and uncertainties and identification of measures which can reduce the probability of such events in the most cost-efficient manner is necessary. This is the challenge that is addressed in this paper.

The structure of the paper is as follows. In Section II the concept of resilience is introduced, specifically mentioning the concept of long-term resilience. Sec II.A describes resilience and resilience metrics more in detail, as well as the shortcomings HILP event analysis based on constructed scenarios. Sec II.B introduces the generation and usage of weather/time-dependent input parameters. Sec II.C describes different visualization techniques for risks with uncertain parameter values. Sec III introduce the method used to generate risk visualizations, and a metric used to identify at which lines hardening measures would have the greatest effects on system's Energy Not Supplied (ENS). Sec IV presents a case study, utilizing the 6-bus Roy Billinton Test System (RBTS), which shows the implementation of the method. The paper is concluded in Sec V.

II. Theory

What constitutes a HILP event is an open discussion. Some consider severe weather a HILP event in its own right, and the associated analysis focus on the impact a constructed weather event has on the power system [4]. Such an approach can have great exploratory value when it comes to unforeseen events but the scenario itself is not associated with a probability. HILP events can also be understood as blackouts, or wide-area power interruptions [5], [6]. In the latter understanding, a HILP event is a set of circumstances leading to component outages which carries with it a high impact on the security of electricity supply. The causal mechanisms leading to the HILP event may be complex in this view but the main components of the analysis is aligned with the traditional risk definition found in [7]: the risk of a scenario is the probability and its consequence. The latter definition may be more appropriate for a risk analysis of HILP events due to its explicit inclusion of a quantified probability.

The scenarios considered in this paper are sets of one or multiple component outages, following the understanding of HILP event as a blackout. Such component outages are often referred to as a contingency. A definition of a contingency, based on [8], is the unexpected failure or outage of a system

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component or sets of system components. A cutset can be defined as a combination of fault events which will result in a top event [9], i.e. a contingency leading to interrupted power. The only system components considered in this paper are transmission lines. It is possible to get a clearer sense of which combination of transmission line outages (scenarios) are more probable through analyzing historical weather patterns. A risk analysis combines this information with the associated consequences. This can be used to prepare emergency plans or prioritize which parts of the grid to strengthen.

Resilience have numerous definitions in the literature and is still continuously developing as a concept. Definitions of resilience generally include two overarching components – robustness and rapidity – referring to a systems ability to withstand a disruptive event and the ability to recover from it [10]. A popular framework for defining resilience is the resilience triangle [11], where the three complementary measures of resilience is the reduction in failure probabilities, reduced consequences from failures and reduced time to recovery. In the domain of power systems the resilience triangle has been extended to a resilience trapezoid [12]: The trapezoid considers how low and fast resilience drops when a weather event hits a power system, how long it resides in a degraded state, and how fast it recovers to its pre-event state.

The authors of [12] also make a distinction between short- and long-term resilience. "*Long term resilience refers to the adaptability of a critical infrastructure to changing conditions and new threats. In power systems, adaptability is achieved through extensive risk and reliability studies, including potential future scenarios to identify the main threats of power system stability. Measures are then applied to when considered necessary for boosting grid resilience to both foreseeable and unexpected events*" [4]. To explore the impact of a system-wide event, in terms of deterioration and restoration of the system, Scenarios of severe weather could be constructed. Constructed scenarios cover limited time-frames – 550 and 750 hours for two different scenarios in [13] – and allows for a relatively high detail of modelling accuracy. A strength of a constructed scenario analysis approach is that it can reveal weaknesses in the system to events which have not previously occurred. A weakness of the constructed scenario approach is that there is limited information about the probability of the scenario itself.

An alternative approach to risk analysis for long-term strategic planning is to rely more on historical weather patterns to uncover potential HILP events, understood as blackouts, rather than constructed scenarios, where the HILP event is the severe weather itself. This is the method employed in this article. Using data of past events and weather patterns over longer time-periods increases the understanding of which components and sets of components are typically simultaneously exposed to harsh weather conditions, and subsequently it will strengthen the knowledge of the probability of the different scenarios. Using a time-series scenario approach comes, however, at the expense of the exploratory strength of the constructed scenario risk analysis, as it only considers past events and weather patterns. It can be argued that a both approaches should be considered for a more complete analysis of long-term resilience.

In [13] a number of solutions increasing the power system resilience is discussed and is divided into two main categories: Operational measures takes advantage of information about a potential external shock and enable appropriate adaptive actions. This could, for example, be network reconfiguration, or tools to increase situational awareness. Hardening measures are focused on the infrastructure resilience, and could include undergrounding of transmission lines, redundant transmission routes, or strengthening the robustness of transmission lines.

Identifying high-risk cutsets can be used to increase situational awareness in the long perspective, enabling preparation and planning of operational measures. Simultaneously, identifying transmission lines which has the largest effect on Annual Expected Energy Not Supplied (AAENS) is a way to prioritize hardening measures. One main purpose of this paper is to contribute to this.

A. *Quantification of risks*

Resilience metrics can be associated with a specific scenario. In [12] a case study is presented which models the effect of a major storm sweeping over the United Kingdom. Four resilience metrics are considered: The speed of grid degradation, the depth of grid degradation, duration of the post-disturbance degraded state, and the speed of which the network recovers. This is quantified for indicators of infrastructure resilience (transmission lines tripped), and operational resilience (generation and load connected).

Sensitivity analyses are further performed in [12] where two scenarios are compared to the base-line development of the HILP event. In the first scenario all components in the grid are made 20 percent more robust. In the second scenario the responsiveness post degradation is increased by 20 percent. Three goals of resilience metrics are given in [14]: "*(1) To provide objective evaluations of the system's current state of resilience. (2) To provide a mean for identification of potential infrastructure vulnerabilities. (3) To enable the evaluation of the changes in the resilience resulting from resilience enhancement activities*". The sensitivity analysis developed in [12] provides measures of the resilience of the system. In [13] the same authors develop a resilience achievement worth (RAW) index, which show the overall system resilience achievement when a transmission corridor is made 100 percent more robust. This is one way of achieving cost-effective resilience enhancement. However, it would also be useful to understand how a percentage decrease in failure rate for a given line would affect the ENS of the system, as hardening measures would have different costs at different levels of robustness increase.

B. *Time-dependent parameters*

Risk of large-scale blackouts due to natural hazards is affected by spatio-temporal correlation in input parameters. A typical example is how a large storm can simultaneously increase both the failure rates and restoration times of multiple components in the grid. Methods and models which capture such effects have been developed, both analytical approaches [15], [16] and numerical approaches based on Monte Carlo simulations [13], [17]–[19].

In [18], [20] methods for calculating time series of hourly probabilities of transmission line failures is presented. The gist of the approach is to use a Bayesian updating scheme to update annual failure rates based on historical failures, before distributing the probability of failure across time by fitting fragility curves to historical weather data. The annual failure rate of the transmission line calculated from the time-series is held equal to the Bayesian updated failure rates through the curve-fitting process.

The resulting time-series of hourly failure probabilities based on historical data can be utilized in multiple ways. A Monte Carlo simulation tool has been developed to evaluate power system reliability using these historical time series [19]. An analytical approach has also been developed to generate time-series of hourly probability of unavailability of components [16]. The latter method gives a time series of the probability of a given component being unavailable. Time-series of unavailability of multiple components can then be combined to evaluate the probability of higher order contingencies (i.e. involving multiple component outages).

Each hourly observation of unavailability must be paired with a consequence for the contingency. This could be done by evaluating the observed operating state in the given hour. An operating state, as defined in [21], is "*a system state valid for a period of time, characterized by its load and generation composition including the electrical topological state (breaker positions etc.) and import/export to neighbouring areas*". This evaluation could be done using optimal power flow (OPF) solutions (see e.g. discussion in [22]).

C. Visualization of risk

To enable appropriate resilience enhancing actions, risks must be communicated to relevant stakeholders, i.e. the system operator. A traditional way of visualizing risks related to specific scenarios have been the risk matrix. The classical risk matrix has two axes representing the frequency or probability of a given scenario, and the associated consequence should the scenario occur, following Kaplan's risk definition [7]. Risk matrices have been a popular tool, although it has some notable drawbacks. In [23] a continuous probability-consequence diagram is proposed as an alternative to risk matrices: The categorical structure of the risk matrix condenses multiple values to a single discrete value, implicitly also suggesting that the actual values does not exceed the bounds of the category. When evaluating time-series with many probability and consequence pairs related to the same scenario, a narrow categorical value could communicate misleading information about both the risk and the associated uncertainty. Introducing uncertainty bands around the central value along both axes, a visual representation of the uncertainty is included.

In [24] further extensions to the probability-consequence diagram was considered and suggested. Specifically introducing an added dimension targeting the strength of evidence. One example can be found in [25]. In their assessment, [24] notes that this added dimension could easily lead to cluttered visual representations. It would also need a structured methodology of calculation. The use of risk diagrams including uncertainty bands is likely to be a good initial representation of risks related to different cutsets.

III. Method

The method assumes that the input data are hourly time series of time-varying unavailability due to different threats, generated using the methods described in Sec II.B. A time series of hourly unavailability of transmission lines, U^l, is paired with time series of interrupted power in different operating states generated by performing a contingency analysis.

The contingency analysis yields a set of cutsets, $CS = \{c_1, c_2, \dots, c_n\}$, where each subset $c = \{l_1, \dots, l_m\}$ contains m elements corresponding to transmission lines. The interrupted power at each load point (LP) for the given cutset is estimated. The interrupted power at each load point is summarized to find the total interrupted power for the system due to a given cutset in (1).

$$P_{interr}^{c} = \sum_{i \in LP} P_{interr}^{LP,c} \tag{1}$$

The unavailability of the cutsets at different time-steps is calculated as the probability of all lines in the cutset being unavailable at the same time. However, cutsets of the second order (containing two elements) may well be subsets of cutsets of the first order, and similarly for higher-order cutsets. To avoid double-counting the probability of a cutset occurring, it is necessary to deduct probabilities of higher order cutsets containing the same elements. Initially, the probability that a cutset occurs is calculated in (2). Then, the probability of the cutsets is adjusted to not account for higher order cutsets containing the same elements in (3), where p denotes the lowest order cutset, and d the higher order cutset.

$$U_o^c = \bigcap_{\forall\, l \in c} U^l \tag{2}$$

$$U^c = U_o^c - \sum_{\forall\, c \in CS |\, m_d = m_p + 1\, \wedge\, c_p \subset c_d} U_o^c \tag{3}$$

The expected Energy Not Supplied (ENS) in the system due to a cutset is a combination of the probability that the cutset occurs and consequence in terms of interrupted power for the system, which is on an hourly basis. This product is annualized, where y is the number of years of observations, to create a measure of historical annual expected ENS (AEENS) in the system due to the cutset.

$$AEENS^{CS} = \sum_{c \in CS} \frac{P_{interr}^{c} \cdot U^c}{y} \tag{4}$$

To identify which lines have the greatest impact on the operational resilience of the system, a component level robustness contribution metric (RCM) is created from the historical data, to identify the effects on AEENS for the system due to potential hardening measures of single components. The RCM is the result of a sensitivity analysis, viewing the impact of a w percent decrease in failure rate of a component on AEENS through all cutsets it is a member of. Conveniently, the failure rate is reflected directly as a factor in the calculation of AAENS, and the sensitivity can be calculated as in (5). The RCM metric can be interpreted as the percentage change in the

$AEENS$ of the system due to a w percent reduction of the failure rate of the evaluated transmission line.

$$RCM^{l} = \frac{\sum_{\forall c \in CS | l \in c} AEENS^{c} \cdot w}{\sum_{c \in CS} AEENS^{c}} \quad (5)$$

IV. CASE STUDY

A test case is performed to illustrate the applicability of the approach. The test case is based on the topology from the Roy Billinton Test System (RBTS) [26], as seen in Fig. 1. Time-series covering 25 years of hourly failure probability due to wind for each transmission line is constructed using the method described in [18] using historical weather data from Norway [27]. 25 percent of the hourly failure rate is assumed to be wind-dependent, while 75 percent is a constant failure rate. Average annual failure rates, seen in Table 1, for transmission lines are kept the same as Permanent Outage Rates (POR) in [26] for both methods. All line failures have a 10-hour outage duration, to keep consistent with the original RBTS line data. This is the basis for constructing time-series of hourly unavailability as described in [16] for the same period, with the simplification that restoration times are assumed to be constant values, rather than distributions. A matching hourly time-series of load demand is generated using the method described in [28], with monthly, daily and hourly variation in demand. The peak load period corresponds to the load data in [26]. This yields 8760 operating states for a single year. The full state-space of transmission line contingencies in each operating state up to the third order are evaluated using a contingency analysis based on an AC Optimal Power Flow (OPF) model for generation rescheduling and load shedding, as described in [28]. The load-shedding priority of the load points in the system were as specified in [29]. This yields an hourly time series of interrupted power for identified cutsets. This time series is repeated to generate 25 years of interrupted power due to the different cutsets.

Risk visualizations and resilience metrics as outlined in Sec. II.B and III are implemented using the constructed time-series. First, visualization of risk due to a cutset, using uncertainty bands is presented. A simplified version of the previous plot is then used to visualize the cutsets with the most extreme hourly risk observations.

Fig 2. show a scatterplot of 25 years' worth of hourly probability of unavailability and interrupted power due to the cutset containing lines 1, 6 and 9. Uncertainty bands, representing the historical maximum and minimum of the observed values along the axes are superimposed on the graph. These bands cross at the average hourly EENS value for the cutset, which forms a center-point sized by the AEENS of the cutset. The graph illustrates how information is concentrated from the actual pair-wise observations of unavailability and interrupted power of the cutset into a risk visualization. The center-point is supported by uncertainty bands, where the hours with the most extreme risk can be found in the upper right corner of the graph.

Fig. 3 shows a similar illustration for the five cutsets of the 2nd or 3rd order with the most extreme hourly risk observations found in the data. Hourly observation points for the cutsets are omitted to avoid cluttering the graph. The axes are on a log-scale, as probability values when comparing cutsets of different orders have a very high spread. The information in this graph shows cutsets which historically have had the highest risk in a single hour.

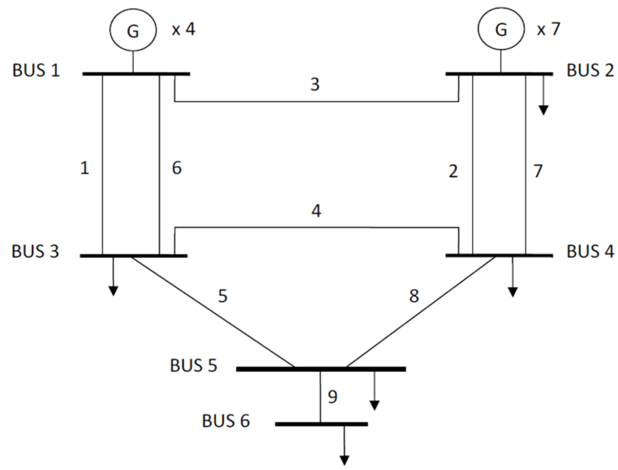

Figure 1: Roy Billinton Test System (RBTS) [26], illustrated in [28].

TABLE 1: RBTS ANNUAL FAILURE RATES

Line (l)	λ
1	1.5
2	5.0
3	4.0
4	1.0
5	1.0
6	1.5
7	5.0
8	1.0
9	1.0

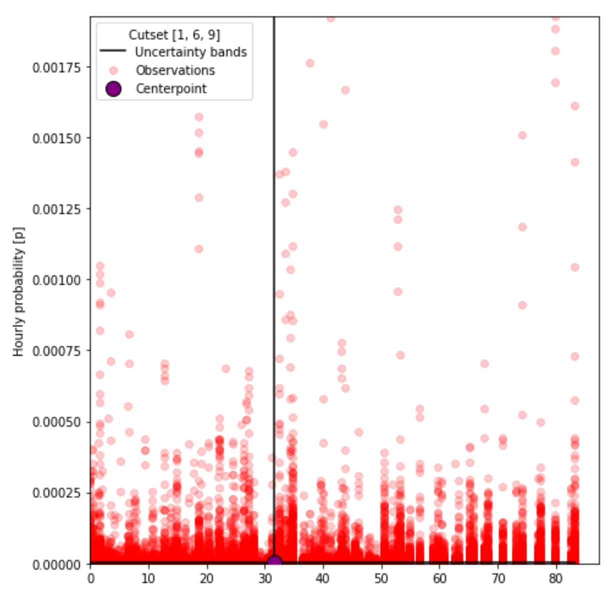

Figure 2: Risk visualization for a single line

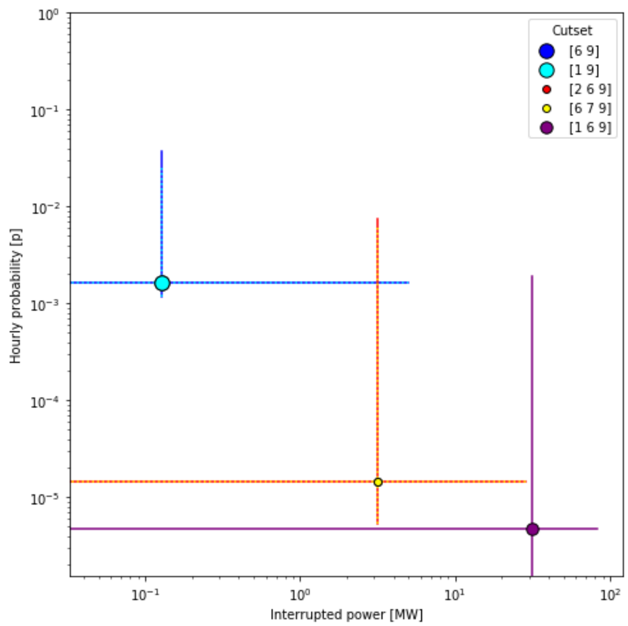

Figure 3: Risk visualization of multiple lines. Log scales.

The calculated resilience contribution measure (RCM) for each line is presented in Table 2, considering the impact of a $w = 10$ percent decrease in failure rate for each line. Transmission line 9 has by far the greatest impact on AEENS in the system. This is not surprising due to the topology of the RBTS, where bus 6 is entirely cut off from the system should line 9 experience an outage. It is also worth noting that lines 1 and 6, which occur in four of the five identified high-risk cutsets follow line 9 as potential targets for hardening measures. The RCM measure can be used to prioritize cost effective hardening measures for the transmission line, thus increasing the resilience of the system.

TABLE 2: RANKED RCM INDICATOR VALUES.

Rank	Line	RCM
1	9	9.306
2	6	0.403
3	1	0.389
4	7	0.215
5	2	0.214
6	5	0.087
7	3	0.086
8	8	0.076
9	4	0.024

Although the depth of the analysis does not cover all conceivable events, those combinations of component outages which are not included in the analysis are subsets of those who are. Reducing the risk of lower order cutsets would therefore also reduce the risk of higher order cutsets, although not explicitly considered nor quantified. The RCM measure could be one such tool to execute targeted grid hardening measures.

V. CONCLUSION

In this paper we have developed methods of identifying risks related to HILP events in the power system. Methods to identify and visualize contingencies which historically have had the highest risk in a single hour have been presented. This could be used to support the development of operational resilience planning, such as emergency plans. To enhance both the operational and infrastructure resilience of the system, a measure of the resilience contribution to the system by decreasing the failure rate of a given line is presented. This could be used to prioritize grid hardening efforts, such as targeted increase in robustness of specific transmission lines. Further work could include combining the RCM measure with priced hardening measures to choose the most cost-effective increase in system resilience within a given budget.

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