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Risk-Informed Operational Planning of Power Transmission Grids: An Overview of Recent Developments

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Abstract

Operational planning of power transmission grids is a complex task which involves a sequence of decision-making problems on different time horizons and over varying degrees of risk and uncertainty. Although there are many studies on power grid operational planning, there is a lack of specific research on recent advancements in Probabilistic Risk Assessment (PRA) and uncertainty modelling options to support this decision-making process. This survey aims to bridge this gap by presenting an overview of recent developments in PRA and risk-informed operational planning for power transmission systems with a specific focus on outage and maintenance scheduling problems. This work highlights the advantages of PRA over deterministic method especially when combined with probabilistic forecasters, estimation methods for low-probability events, and high-fidelity simulators. A discussion of major challenges and current limitations of PRA methods is also proposed, and a prospective view of future research directions is introduced. Advanced PRA approaches have the potential to improve the sustainability and resilience of future power grids by enabling informed risk-informed operational scheduling for both short-term and long-term planning horizons.

Keywords: PRA, Power Grid, Operational Planning, Outage, Forecast, Uncertainty, Rare Events

1. Introduction

Operational planning of power transmission systems is a fundamental discipline whose main scope is identifying operational decisions that ensure the stability, quality, and profitability of the energy transmission service. Operational planning decisions are taken over different planning horizons and determine the downtime of components and subsystems which need upgrading, maintenance, or refurbishment, like transmission lines, substations, and power plants. Traditionally, deterministic security-constrained optimization methods prescribe outage schedules one year ahead and N-1 deterministic security constraints are applied to guarantee safe operations during scheduled downtimes (Zhang, 2022). Because grid operations change dynamically and system safety is paramount, the scheduled operational plans must be revised regularly.

Emerging trends in power transmission grids are posing new challenges for traditional deterministic operational planning approaches, with the potential to undermine the safety of the grid. The growing integration of renewable energy sources, changes in loads driven by the electrification of mobility services, increasing frequency of extreme weather events potentially leading to unforeseen N-k failures and instability events (Wen, 2023), and the decentralization of the energy market are some of the recent challenges which are adding new risks and uncertainties in the grid operations. These new risk sources have pushed the power engineering community to develop advanced approaches incorporating online monitoring data into probabilistic and risk-informed operational planning strategies. See the recent works of (Metwaly, 2020), (Karmakar, 2020), and (Varbella, 2023) for examples of applications. Probabilistic risk assessment approaches and probabilistic operational planning strategies have gained particular attention in the last year as powerful tools to address these challenges (Vaiman, 2011, Ciapessoni, 2016, Liu, 2023). In contrast to deterministic planning approaches, PRA quantifies and distinguishes between the likelihood of occurrence of different scenarios and the severity of the system, thus allowing for informed decisions and better management of the available resources and identified hazards. In this work, we present a survey of latest trends and new developments concerning PRA and risk-informed approaches for the operational planning of power transmission grids. Specifically, we focus on robust methodologies to address uncertainty issues concerning future system states and novel approaches for the efficient estimation of low probabilities of rare failure events and simulation-based assessment of severity and consequences for these events. PRA approaches could enable informed decision-making under uncertainty and the integration of risk metrics and risk forecasters within short and mid-term planning pipelines could enhance the resilience, reliability, and sustainability of future grid operations.

The remainder of this work is structured as follows: Section 2 introduces the operational planning and outage scheduling problem for power grids. Section 3 reviews PRA, severity scores, recent developments in rare event estimation, epistemic uncertainty quantification and extreme event modelling. Sections 4 and 5 close the paper with a brief discussion and recommendations for future research.

2. Operational planning and outage scheduling problem

Operational planning is a process that aims to maintain effective power delivery while ensuring system adequacy and operability under various scenarios. (Qiu, 2022) present a comprehensive review of power system scheduling problems and robust optimization approaches to deal with uncertainties. Four classes of operational planning problems are considered: Economic Dispatch (ED), Unit Commitment (UC), Power Coordination (PC) and Robust dispatch (RD) problems. Albeit broad and quite comprehensive, this review did not explicitly address the outage scheduling (OS) problem, also known as the maintenance scheduling problem, which is a fundamental task in transmission grid operational planning.

The adequacy of a power grid defines the system's ability to supply enough energy and meet the aggregated electrical demand of the end-users (under both normal system states and planned failure scenarios). One of the main goals of an OS problem is to ensure that changes in the system adequacy and safety induced by planned contingency will remain within an acceptable level through the planning horizon. OS decisions, such as repairs, upgrading, refurbishment, and decommissioning of grid elements (Anders, 2003), can significantly impact power transport capacity and quality of power delivery. These outages are timely planned over a yearly horizon and later updated to meet requirements on mid-term (monthly) and short-term (daily and real-time) horizons. During this process, transmission system operators must forecast grid states and re-evaluate the feasibility of a planned outage if this could compromise security (Fu, 2007). Preventing future grid congestion, meeting dynamic grid stability criteria while minimising environmental impact and ensuring a positive cost-benefit ratio are some of the key principles driving operational planning strategies for future grids.

The OS problem involves risks and uncertainties due to the complexity of predicting future grid states and undesirable consequences (potentially severe) of erroneous plans on the system's stability and security (Froger, 2016). Despite the pivotal role that both risk and uncertainty play in this process, maintenance schedules are often defined by deterministic security-constrained optimization models in practical applications, which can result in sub-optimal solutions in terms of both operational cost and safety. Hence, research efforts have focused on developing robust PRA frameworks, like the early work of (Jiang, 2002) where an IMSS - Integrated Maintenance Selector and Scheduler, was introduced for a risk-informed selection model for refurbishment actions on bulk transmission equipment. This approach addressed some of the limitations of deterministic OS approaches by exploiting a cumulative long-term risk estimator, i.e., a risk index derived from the failure of various components and a Markovian probabilistic model for the failure probabilities. The authors concluded that risk-based procedures hold significant potential for better managing ageing assets. However, the prescription of an accurate probabilistic (Markov) model may require a large volume of data and/or extensive simulations, which are not always available or feasible in practice.

Recently, (Dalal, 2019) introduced a chance-constrained approach for outage scheduling supported by machine learning (ML) surrogate models, i.e., proxies. The authors claim that the completely data-driven nature of this approach highlights a significant advancement in the field since their ML approach does not require a stochastic model and uses less unwarranted probabilistic assumptions. Although the risks and severities of different actions were not directly addressed by (Dalal, 2019), this shift towards data-driven methodologies marks a notable departure from traditional approaches, offering promising avenues for enhanced operational planning and PRA for power transmission systems. In a similar line of research, (Toubea, 2022) introduced an ML-assisted OS framework to support maintenance activities in power systems. ML models have been developed as surrogates to predict the outcome of contingency analysis and thus reduce computational time and alleviate tractability issues arising from the need to comply with operational security standards. The interested reader is reminded of the works of (Froger, 2016) and (Alimi, 2020) for a review of ML approaches supporting transient stability, voltage stability and power quality disturbance analyses and for a complete review of mathematical optimization frameworks for maintenance scheduling in the electricity industry. In the following sections, we provide an overview of deterministic security-constrained OS planning and discuss the challenges associated with moving from deterministic planning approaches to probabilistic risk-informed planning.

2.1. Deterministic security-constrained OS problem

Consider a power grid comprising N components of which $M < N$ require maintenance in a fixed planning horizon of length T. The planning horizon is assumed to be composed of fixed cycles $t \in \{1, \dots, T\}$ and, for each t a subset of components can be taken out-of-service so that maintenance can be performed, e.g., by upgrading, repairing, or refurbishing the element. A maintenance policy $\pi \in \Pi$ is defined as a sequence of maintenance actions $\pi = (\pi_1, \pi_2, \dots, \pi_T)$ over the planning horizon, where $\pi_t = (\pi_{1,t}, \dots, \pi_{M,t})$ is the set of components that are maintained at the cycle t, such that $\pi_{t,k} = 1$ if component k is disconnected and 0 otherwise. The objective of the OS problem is to find an optimal maintenance policy $\pi^\star \in \Pi = \{0,1\}^{M\times T}$ such that:1) the total operational cost of the T-length cycle is minimized, 2) a cumulative risk score of the T-length cycle is minimized and 3) guarantees coverage of a minimum set of required maintenance actions while complying to budget and technical constraints on security and required downtimes. A simple security-constrained OS optimizer is given by:

$$\pi^\star = \underset{\pi\in\Pi}{\operatorname{argmin}} \sum_{t=1}^{T} C_o(\pi_t, x_t), \tag{1}$$

subject to budget and security constraints as follows:

$$\sum_{t=1}^{T} C_M(\pi_t) < C_{budget}, \tag{2}$$

$$f_{sec}(\pi_t, x_t, c) < 0 \;\; \forall\, c \in \mathcal{C}_{N-1}\,, t \in \{1, \dots, T\}, \tag{3}$$

$$\sum_{t=1}^{T} \pi_{t,k} = b_k\,,\;\; k = 1, \dots, M. \tag{4}$$

C_{op} is the operational cost of the grid to be minimized, C_M is the cost of maintenance constrained by a maximum budget, $f_{sec}(\pi_t, x_t, c)$ defines security constraints (for instance line overflow limits) that must be always upheld and for all the single-component failures in a contingency set $\mathcal{C}_{N-1}$ and times $t \in \{1, \dots, T\}$ in the planning horizon. The last equality constraints ensure that the at least b_k maintenance cycles are allocated to the M components. See the work of (Maquirriain, 2023) for a heuristic solution of a general maintenance scheduling problem under the assumption of single-component maintenance at each cycle t. This optimization problem is high-dimensional because M can be large and planning horizon extends up to one year. Moreover, because the conditions x_t are inherently uncertain and the security constraints only focus on a limited set of initiating events (single-component failures), this deterministic approach will likely fail to capture the full spectrum of potential failure modes and their interdependencies within the grid. Deterministic methods typically lack the ability to differentiate between the probabilities of different contingencies and all failures are treated equally, thereby neglecting valuable information on component reliability, as well as the different consequences and possible unwarranted outcomes for the system. This oversight can lead to suboptimal decision-making and inadequate resource allocation for risk mitigation and prevention.

2.2. Risk-informed OS and operational planning

In contrast to deterministic approaches, PRA offers a more comprehensive understanding of hazards and related uncertainties by integrating probabilistic modelling and severity evaluation techniques. PRA has gained attention among researchers in operational planning and optimization because offer a systematic framework for evaluating the likelihood and consequences of various failure scenarios. This represents a significant departure from deterministic methods, which often overlook crucial uncertainties related to future weather conditions and rare operational states and failures. Hence PRA could enable utilities and operators to systematically assess the probabilities and consequences of various scenarios, considering a broader range of initiating events, planned outage schedules, and their potential impact on the transmission grid. By capturing uncertainties in the grid's operation and weather patterns, PRA can inform decision-makers with a more accurate view of the risk exposure and consequently, the decision-maker can prioritize risk mitigation efforts more effectively while enhancing grid resilience and sustainability. In the work of (Jiang, 2002), the authors tried to extend the OS problem by including probabilistic cumulative risk reduction indicators in the objective function. A formal definition of probabilistic risk and a discussion on strengths and limitations is presented next.

3. Probabilistic Risk Assessment and risk definition

Risk is traditionally defined as the combination of probability (or frequency) of disturbances and magnitude/severity of their consequences. The combination of the probability of hazardous power grid operational states and a vulnerability metric given the occurrence of the hazard. A mathematical definition of dynamic risk indicator is given as follows (Rocchetta, 2020):

$$R(\pi_t, x_t) = \int_{x \in \mathcal{X}_\mathrm{t}} \sum_{c \in \mathcal{C}} \mathbb{P}(x)\mathbb{P}(c|x, \pi_t) Sev(x, c, \pi_t) dx, \tag{5}$$

where R denotes the operational risk at the next time t expressed as a function of the planned maintenance actions π_t and stochastic operational-environmental condition $\mathrm{x_t}$ which are distributed according to $\mathbb{P}(x)$ in a plausible set $\mathcal{X}_\mathrm{t} \subset \mathbb{R}^{n_x}$ of system states. $\mathbb{P}(c|x, \pi_t)$ is the conditional failure occurrence probability given for the scenario x and the OS policy and $c \in \mathcal{C}$ are contingency events (disturbances) in a contingency set $\mathcal{C}$.

This risk indicator in equation (5) overcomes the limitations of traditional deterministic approaches by explicitly accounting for the likelihood of unexpected failures, diverse environmental-operational conditions, as well as an indicator of the consequences and severity given by $Sev(x, c)$. Despite the many advantages, there are also several challenges that must be addressed in the computation for an effective and efficient computation of the risks $R(\pi_t, x_t)$ and transition from deterministic to a risk-informed operational planning approach.

In particular, the following challenges are identified and discussed in the remainder of this work:

- The contingency set $\mathcal{C}$ can encompass not only the unexpected loss of single components, denoted as, $\mathcal{C}_{N-1}$ but also be extended to include failure sequences (cascading events) and N-k contingencies (common cause failure), such that$\mathrm{c} = \{\mathrm{c_1}, \mathrm{c_2}, \ldots \mathrm{c_k}\}$. However, the definition of representative set $\mathcal{C}$ is a difficult combinatorial problem. It may require evaluating the risks covered by failures within the set, relying on heuristics supported by expert opinion.
- The severity score $Sev(x, c)$, implicitly defined in this work, can consist of a vector with multi-dimensional indicators of social, environmental, economic, and systemic consequences of failures on the grid. Selection of appropriate score may be a problem-dependent task and must align with the objective of decision-making informed by the PRA. A brief overview of different severity indicators presented in section 3.1.
- The severity assessment often requires simulation-based analysis of the grid response to the conditions x, c and power flow, transient stability, and cascading failure models have been developed to address this task. However, simulators can be computationally intensive to run, in turn leading to tractability issues especially if the set $\mathcal{C}$ is large and a standard Monte Carlo employed for the probabilistic integration. Surrogate models (emulators/proxies) have been specifically developed to address this challenge, see for instance, (Varbella, 2023) and (Rocchetta, 2020).
- The estimation of $\mathbb{P}(x)$, $\mathbb{P}(c|x, \pi_t)$ and domain $\mathcal{X}_\mathrm{t}$ for the probabilistic integration can be a challenging task which require a large volume of contingency and operational data. ML-based forecasting tools can be developed to support these estimations; however, it is important to note that rare failure and operational scenarios have a small probability of occurrence, and data will be inevitably scarce thus limiting the efficacy of data-driven approaches.
- Rare events are neglected by traditional approaches. However, these events may be non-negligible from a risk perspective due to the high severity score $Sev(x, c)$. Hybrid forecasting methods, which combine data with physics-based modeling of grid failures, along with advanced probabilistic samplers, could address this challenge. See for instance the works of, e.g., (Zio, 2008) and (Chan, 2023), and to section 3.2.3 for a more detailed overview.

Advanced PRA for risk-informed outage scheduling must account for the lack of information and failure data by combining available data with advanced forecasting tools for uncertainty quantification and high-fidelity simulators to reduce epistemic uncertainty and compensate for data scarcity.

3.1. Severity scores and risk indicators

Power grid risk indicators and can be categorized as follows (Che-Castaldo et al., 2021): I) Financial, II) Environmental, III) Systemic. Financial indicators assess the economic impact of potential risks on the power grid, including costs associated with equipment damage, downtime, and revenue loss. Environmental indicators evaluate the environmental impact of disturbances. These include severity scores like total CO2 emissions, habitat disruption, water contamination. Systemic operational risk indicators are perhaps the most widely investigated in the literature and focus system-specific indicators. A few examples of servery indicators which have been used for online PRA and for economic dispatch include overall severity scores, voltage deviations, frequency deviations, and other operational anomalies that could potentially compromise the quality of the power delivery and stability of the grid. For a comprehensive overview of topological vulnerability scores the interested reader is reminded to (Abedi et al., 2019). For a review of operational risks and resilience indicators the reader can refer to (Panteli, 2017 and Rocchetta, 2019).

Traditional operational planning for transmission grids often overlooks the potential impacts of extreme scenarios which, despite their historical rarity, can lead to significant disruptions in grid performance, resulting in high severity $Sev(\mathrm{x}, c)$. In response to this challenge, various frameworks have been developed in the literature to evaluate the consequences of such rare events. These frameworks include modelling of weather-induced failures (Rocchetta, 2018) and extreme weather events (Lian, 2023), severity estimation of lighting-induced common cause failures using fragility models (Wang, 2023), cascading outages (Li, 2017), and transient instabilities (Sobbouhi, 2021). On a similar line of research, (Guo, 2020) proposed a multi-state model for enhancing transmission system resilience against short-circuit faults caused by extreme weather events, highlighting the importance of proactive planning. (Kumar, 2021) introduced a novel framework for risk and resilience assessment of critical infrastructure towards climate change, emphasizing the need for adaptive strategies. (Quiring, 2014) analysed the impact and severity of tropical cyclones and related hazards, (Henneaux, 2015) proposed a two-level probabilistic risk assessment of cascading outages, whilst (Han et al. 2021) introduced an assessment framework for the evaluation of multi-meteorological disasters. These studies underscore the critical role of advanced modelling approaches in enhancing grid resilience against extreme events. (Hu et al, 2023) focused on risk-informed resilience planning of transmission systems against ice storms, demonstrating the necessity of incorporating extreme weather scenarios and dedicated modelling tools to model specific hazard sources and advance the planning processes. In (Li, 2017) the authors a multiregional, multi-industry interdependence model to quantify the short-term economic impact of power cascading failures. Recently, (Varbella, 2023) built upon the work of (Li, 2017) and developed a data-driven methodology for online estimation of the risk of cascading failures. Graph neural networks and ML-driven surrogates are the enabling technologies used to achieve online estimation capabilities.

3.2. Uncertainty Quantification

Uncertainty quantification (UQ) is indispensable for achieving effective PRA and informing operational planning and outage scheduling strategies. In the conceptual risk framework, UQ plays a crucial role in quantifying uncertainty and, where feasible, reducing it. It provides a means to estimate the probabilities $\mathbb{P}(x)$ and $\mathbb{P}(c|x, \pi_t)$ as well as the epistemic uncertainty affecting these estimators. In the work of (Aien, 2016), a comprehensive review of UQ approaches for power system analyses is proposed and particular focus dedicated to decision-making problems. Modelling approaches are revised and classified in such as probabilistic, possibilistic, and generalized UQ methods, e.g., as for information gap decision theory and robust risk-informed optimization approaches. Similarly, the project (GARPUP, 2017) delved into computational models and UQ but with particular focus on applied PRA for transmission systems. Among the other targets, the project aimed to develop tools to predict the location, duration, and amount of power supply interruptions. This project specifically addressed different decision-making aspects for the transmission grid, encompassing power system operation, asset management, and system development. These two works, thoroughly discusses modelling approaches for decision-making under uncertainty in power grids. However, they also lack a precise categorization of uncertainty sources affecting $\mathbb{P}(x)$ and $\mathbb{P}(c|x, \pi)$ and modelling approaches that are tailored to the mathematical definition of risk presented above. To facilitate a comprehensive analysis and future PRA developments, the work proposes a survey of the following methodological areas: (i) environmental-operational state forecasters; (ii) modelling of extreme weather conditions, common cause failures, and cascading outages; and (iii) quantification of epistemic uncertainty.

3.2.1. Forecasters for environmental-operational states $\mathbb{P}(\boldsymbol{x})$

Accurate estimation of $\mathbb{P}(\boldsymbol{x})$ is essential to estimate the risk in equation (5), thus ensuring effective PRA and risk-informed operational planning. Forecasting tools can offer valuable support to address this challenge and several methods have been recently proposed, for instance, to predict the aggregated and nodal load demand and renewable energy generation (Nespoli et al., 2020), and for heterogeneous environmental conditions and weather-induced failures (Dokic et al., 2019). By integrating forecasting models, PRA approaches can anticipate future system conditions, enabling proactive risk management strategies and adaptation of operational planning decisions. The primary objective of forecasting models is to give precise predictions of key operational-environmental factors x, hence facilitating risk estimation, risk-informed decision-making, and risk mitigation measures. Forecasters can be divided into deterministic and stochastic models (Xie, 2023) based on whether predictions for the future environmental-operational conditions are given as a point-expectation $\hat{x} = \mathbb{E}[x]$ or as a distributional model such that $x \sim f(x)$, that is, the next operational conditions are distributed as a joint probability density function (PDF) of $f(x)$. Forecasting tools play a crucial role in supporting a model-based estimation of failure probabilities. These tools provide valuable insights into future environmental-operational conditions, essential inputs for assessing the likelihood of failure events. By leveraging forecasting models, analysts can enhance their understanding of system dynamics and uncertainties, enabling more accurate and informed estimations of failure probabilities and enhanced PRA (Zio E. 2018). For an overview of modelling approaches for representing the uncertainty in markets for operational planning and forecasting of renewable power systems see (Haugen, 2023)

3.2.2. Simulation-based failure probability estimation

Consider a classical definition of contingency probability:

$$\mathbb{P}(c) = \int_{x \in \mathcal{X}_t} I_c(x) f(x) dx = \mathbb{E}[I_c], \tag{6}$$

where c is a failure event and x is vector uncertain operational-environmental conditions, $f(\mathrm{x})$ is the joint PDF, and $I_c(\mathrm{x})$ is the indicator function for the failure condition such that $I_c(\mathrm{x}) = 1$ if the failure event occurs and 0 otherwise. Because the contingency probability is a multi-dimensional integral and is not tractable analytically, integration methods like MC are often used to estimate the failure probability by sampling N realizations of the uncertain factors from $f(\mathrm{x})$ and averaging $\mathbb{P}(\mathrm{c}) \approx \frac{1}{N}\sum_{i=1}^{N} I_c(\mathrm{x}_i)$. Evaluation of the indicator function for a failure condition $I_c(\mathrm{x})$, implicitly defined here for brevity's sake, generally requires a simulation-based evaluation of the system response to a scenario x, e.g., by means of high-fidelity simulators combining power flows simulators of cascading failures (Gjorgiev, 2022), and/or transient instability models like (Umair, 2022) or (Sobbouhi, 2022). If the probability of failure is small or the system function $I_c(\mathrm{x})$ is numerically costly to evaluate, a crude MC integration becomes very time-consuming. Hence, efficient sampling strategies must be therefore considered to alleviate the computational burden.

3.2.3. Efficient analysis of low-probability events

This section provides a brief overview of rare-event estimation methods which are essential to achieve efficient assessment of low-probability, high-impact, events for PRA and risk-informed transmission grid planning. These methods encompass a range of statistical techniques, simulation-based approaches, and computational algorithms designed to efficiently estimate the likelihood of rare scenarios. The most widely applied approaches include Markov Chain Monte Carlo methods, Extreme value theory, and other advanced sampling methods like Subset Simulation (SuS), Importance Sampling (Cadini, 2017), and adaptive Monte Carlo methods (Chan, 2022). Advanced algorithms that integrate ML techniques have also been increasingly applied to tackle the rare-event estimation problem because of their efficacy in handling complex data structures and nonlinearities. A few representative examples of approaches applied in the power grid operational planning domain include adaptive SuS methods (Chan, 2022), Bayesian improved cross entropy models (Chan, 2023). Recently, methodological advancements for rare event simulation have been also proposed using ML, such as SuS for high dimensional spaces (Zuev, 2012 and Zuev, 2015), methods based on LSTM neural networks (Oh, 2021) and SuS combined with Hamiltonian networks (Thaler, 2024). Specifically for the SuS method (Zio, 2008, Hu, 2014), the key idea is to express a small failure probability as a product of larger conditional probabilities by introducing intermediate failure events. Mathematically, the subset method converts the probability of a rare, like the probability of grid failure due to instability P_c, into product of larger conditional probabilities, $P_c = \prod p_{c_i}$, where the probabilities

p_{c_i} are estimated sequentially from nested subsets of intermediate failure domains $\mathbb{R}^{n_x} = F_0 \supset F_1 \dots \supset F_k = F$. The domain $F = \{x \in \mathcal{X}_t \mid I_c(x) = 1\}$ is the target failure region whilst F_i are intermediate failure domains for the levels $i = 1,2, \dots, k$. $\mathbb{R}^{n_x}$ is the space of the uncertain parameters which could be reduced to $\mathcal{X}_t$ if an accurate predictor of the support domain for the uncertain parameters is provided. This type of advanced probabilistic analysis extends particularly well to the analysis of cascading failures. For instance, consider a black out event defined by the loss of k components in the grid. The failure components define a contingency set $\{c_1, c_2, \dots, c_k\}$ and the probability of this event happening is $P_c = \mathbb{P}(c_1, c_2, \dots, c_k)$. This probability is unknown and very small in practice, making its efficient estimation difficult using traditional sampling methods. On the other hand, this event can be expressed as a sequence of events having larger failure probabilities, for instance, a of primary failure events with a single component failure $p_{c_1} = \mathbb{P}[c_1]$ and the conditional failure probabilities of secondary events in the cascading sequence. This yields the following decomposition of the low-probability events in a sequence of larger conditional probabilities as follows, $P_c = \mathbb{P}(c_k|c_2, \dots, c_{k-1}) \times \dots \times \mathbb{P}(c_3|c_2, c_1) \times \mathbb{P}(c_2|c_1) \times \mathbb{P}(c_1)$. Figure 1 present a conceptual example of this probabilistic decomposition method.

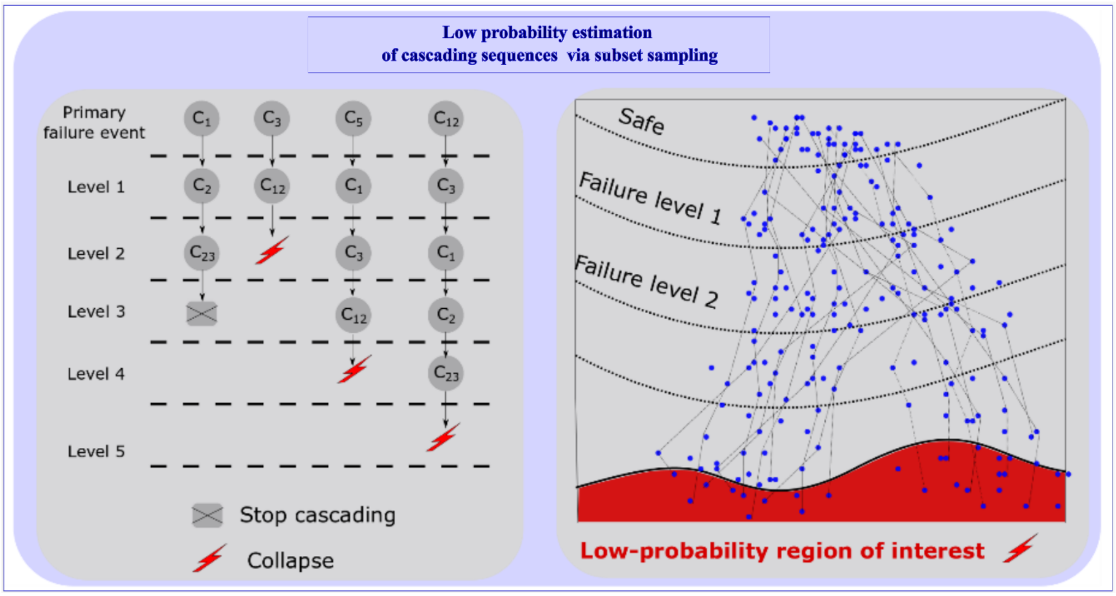

Figure 1: An illustrated example of the SuS procedure for estimating the probability of low probability cascading failures.

3.2.4. Epistemic uncertainty quantification

When databases contain missing information or the database is small, the effect of epistemic uncertainty on the density $f(x)$ can be exceptionally large. Traditional probabilistic methods and forecasters may struggle to cope with imprecision; due to a limitation of classical probability theory which models epistemic uncertainty using probabilities. This can lead to overconfidence in the true probability of facing a contingency increasing the grid's operational risks and costs. In fact, the true PDF $f(x)$ is always unavailable in practice, because of finite data and information. Hence, model assumptions may be required and a probabilistic estimator of P_c will be inevitably affected by these assumptions. Generalized UQ methods overcome these difficulties and quantify the epistemic uncertainty in P_c. Methods based on advanced UQ and statistical reasoning in ML have been proposed for this, see (Hüllermeier, 2021) and (Rocchetta, 2023) for an overview of different approaches and (Liu, 2021) for a review of generalization for out-of-sample data and distributional shifts. However, only a limited number of works applied generalized UQ approaches to assess the robustness of PRA results for power grids. An imprecise probabilistic framework for risk assessment was proposed by (Rocchetta, 2020), and imprecision affecting vulnerability and severity assessment was investigated in (Rocchetta, 2018). Within this scope, fuzzy analytic methods for the risk assessment of transmission lines affected by multi-meteorological disasters have been also investigated in (Han, 2021) and a scenario theoretic approach for economic dispatch with tuneable risk levels studied (Modarresi, 2018). To the best author's knowledge, the literature lacks an application of these advanced concepts to risk-informed optimization maintenance schedules of power transmission grids.

4. Prospective on future research

Probabilistic risk assessment (PRA) and risk-informed planning in power transmission systems represent a notable departure from conventional deterministic methods, providing a better understanding of risks, consequences of unforeseen failures, and operational-environmental uncertainties affecting the grid. Accurate PRA can provide a clearer view of issues related to future power grid instabilities, topological weaknesses, and consequences and likelihood of rare scenarios. Importantly, a risk-based identification of root cause events and low-probability/high-consequence failures can help to prevent and mitigate the effect of new instability events and cascading failures and provide better operational planning strategies. However, the adoption of PRA also introduces many challenges since the inclusion of probabilities and severity scores aggravates the computational cost of an already complex combinatorial optimization/planning problem. Specifically, technical challenges related to the efficient estimation of low-probability events (like cascading failures), lack of representative failure data, and computational tractability of high-fidelity simulators must be addressed. This work presented an overview of recent works and developments towards these directions. Novel machine learning approaches for forecasting, surrogate models, and efficient methods for the estimation of low-probability evens proved to hold high potential and have been recently explored to advance the PRA of power grids. Quantification of the epistemic uncertainty affecting planning strategies, stemming from the scarcity of rare failure data and model imprecision, and the development of a tractable risk-informed optimization model for operational scheduling are also crucial and require further investigation. Addressing these challenges mandates efficient estimation of low-probability events, rectifying deficiencies in failure data representation, and ensuring computational tractability in dynamic analysis using high-fidelity simulators.

5. Discussion and preliminary conclusions

This work reviewed some of the latest trends and developments with PRA and operation planning of power transmission grids, particularly focusing on computational challenges associated with probabilistic risk assessment methods and with the transition from deterministic outage scheduling approaches to probabilistic risk-informed models. Some of the most pressing issues have been highlighted and discussed, such as the estimation of rare events and extreme failure scenarios, the definition of probabilistic operational forecasters, efficient simulation-based assessment of the different consequences of failures, and epistemic uncertainty quantification of the resulting risk scores. By addressing these challenges, researchers and practitioners could better understand risk and mitigate the risks associated with grid operation, ultimately enhancing the reliability and performance of outage scheduling actions.

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