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Towards Risk-Informed Transmission Grid Outage Planning

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Power grid outage planning is a class of preventive maintenance (PM) problems whose main objective is the optimal allocation of maintenance activities, such as component repairs, refurbishments, and upgrades. To ensure safe operations during maintenance, N-1 security constraints are commonly enforced, creating robust preventive maintenance plans against single-component failures. While uncertainty has been addressed extensively in the PM optimization literature, many grid outage planning approaches are deterministic. Deterministic security-constrained outage planning problems, due to their combinatorial nature, are challenging problems, and incorporating uncertainty can further increase the computational burden and challenge numerical tractability. However, omitting sources of uncertainty can compromise the cost-effectiveness and safety of the plan. This work addresses this gap by introducing a risk-informed approach to power grid outage planning that accounts for operational and planning uncertainties. We present an illustrative case study of a planning problem under uncertainty based on our previous work on risk-informed optimisation. We discuss the benefits and drawbacks of the proposed risk-informed approach and speculate on further extensions for power grid outage planning and related problems.

Keywords: Power grid, Outage scheduling, Uncertainty, Risk, Maintenance, Optimization.

1. Introduction

Power grid outage planning (OP) are preventive maintenance problems that focus on the optimal allocation of maintenance activities, such as component repairs and upgrades. Ensuring safe grid operations while scheduling long-term PM is of paramount importance. To achieve this objective, N-1 security constraints are typically enforced, preventing overloading and instabilities for any (unplanned) single component failure Wang et al. (2015). This class of problems is also referred to as security-constrained OP problems (SCOP).

In the existing literature, most of the available works on SCOP rely on deterministic approaches Sharma et al. (2011); Vassiliadis and Pistikopoulos (2001); de Jonge and Scarf (2020), where the major sources of uncertainties are neglected. Only a limited number of works include uncertainty within their formulations, particularly relying on stochastic programming approaches Rocha et al. (2023); Wu et al. (2010).

The inclusion of uncertainty in SCOP formulations is a challenging task, as it can considerably increase the computational burden. In fact, deterministic SCOP present already significant computational challenges due to their combinatorial nature, making them prohibitive for large systems Eygelaar et al. (2018). In order to address this issue, various alternative approaches have been proposed, such as population-based methods Hadavi (2008); Zanghi et al. (2012), decomposition approaches Rodríguez et al. (2021) and heuristics Kralj and Petrovic (1995); Gubin et al. (2023).

Since PM activities are scheduled over a prolonged period of time (typically several months), omitting sources of uncertainty when optimizing these activities can lead to poor performance and unsafe grid operations. In this paper, we explore the inclusion of uncertainty in SCOP by introducing a risk-informed SCOP approach. Risk-informed frameworks have known limited applications in the field of power grids, with the notable exceptions of the seminal works of Jiang et al. (2002, 2004) and the more recent advancements by Eygelaar et al. (2018).

To address this gap, we investigate the inclusion of uncertainty in power system OP problems through a data-driven, risk-informed approach. Taking advantage of the growing availability of open data, we propose a novel framework for OP problems that incorporates uncertain, risk-based operational constraints. First, drawing on our previous work Rocchetta et al. (2024), we introduce the concept of risk-informed optimization and its relationship to traditional optimization approaches under uncertainty. Second, we present an illustrative case study, applying the proposed framework to an OP problem under uncertainty, and discussing its benefits and limitations. Finally, we outline potential extensions of the risk-informed framework for OP and related problems, offering pathways for future research.

The rest of this paper is organized as follows: in Section 2, we describe the deterministic version of the SCOP problem; in Section 3, we present the proposed risk-informed approach; in Section 4, we outline the illustrative case study; in Section 5, we present the preliminary results; in Section 6, we provide preliminary conclusions and possible extensions.

2. Deterministic SCOP problem

A power transmission grid comprises a set of N components, including n_B busses, n_L transmission lines, n_G generators, transformers, etc. A SCOP problem addresses the scheduling of PM activities on a subset of these N transmission components. These PM activities must be scheduled such that a generation-demand balance is achieved, capacity constraints are satisfied, and safety-related constraints, including unplanned N-1 contingency scenarios, are accounted for. While security-constrained deterministic formulations provide a powerful tool for scheduling PM activities in power grids, they neglect any source of uncertainty about future operational states, including contingencies and demand deviations. Our work investigated two formulations: a deterministic SCOP (det-SCOP) and risk-informed SCOP to embed within the problem information from a probabilistic risk assessment model to prescribe more reliable and cost-efficient PM schedules.

2.1. *The proposed det-SCOP formulation*

Consider a set of n_O components that require maintenance (planned outages) $\mathcal{O} = \{o_i\}_{i=1}^{n_O}$, a set of n_C unplanned failures (contingencies) $\mathcal{C} = \{c_i\}_{i=1}^{n_C}$, and a discretized set of n_T planning steps $T = \{t\}_{t=1}^{n_T}$ within a planning horizon (e.g., one year). The main objective of the SCOP problem is to define a schedule, or timetable, for the n_O maintenance activities while adhering to operational, budget, and safety constraints.

2.1.1. *Outage plan and variables*

The decision variables in the SCOP formulation are defined as

$$\boldsymbol{X} = (\boldsymbol{X}_{\text{PM}}, \boldsymbol{X}_{\text{plan}}, \boldsymbol{X}_{\text{cont}}),$$

which comprises three main components, i.e., outage planning variables, $\boldsymbol{X}_{\text{PM}}$, operational variables in normal planned outage states, $\boldsymbol{X}_{\text{plan}}$, and operational variables under unplanned contingency states, $\boldsymbol{X}_{\text{cont}}$.

Planned outage $\boldsymbol{X}_{\text{PM}} = (\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{e})$:
Here $\boldsymbol{x} \in \{0,1\}^{n_T \times n_O}$, is a binary matrix representing the scheduled timetable for the PM activities, such that $x_{t,o} = 1$ if outage $o \in \mathcal{O}$ is scheduled at time t, and 0 otherwise. Similarly to $\boldsymbol{x}$, binary matrices $\boldsymbol{s}, \boldsymbol{e}$ represent the starting and ending indicators for the PM activities, respectively.

Normal states $\boldsymbol{X}_{\text{plan}} = (\boldsymbol{P}_G, \boldsymbol{f}, \boldsymbol{\zeta})$:
$\boldsymbol{f} \in \mathbb{R}^{n_T \times n_L}$ represents the line flow matrix, with $f_{t,l} \in \mathbb{R}$ being the flow at line l at time t; $\boldsymbol{P}_G \in \mathbb{R}^{+, n_T \times n_G}$, is the non-negative power generation matrix, with element $P_{t,g}$ defining the power generated by g at time t. The variables $\boldsymbol{\zeta} \in \mathbb{R}^{+, n_T \times n_B}$ are non-negative nodal demand-supply gaps, i.e. the load shedding.

Contingency states $\boldsymbol{X}_{\text{plan}} = (\boldsymbol{P}_{G,C}, \boldsymbol{f}_C, \boldsymbol{\zeta}_C)$: Same variables defined for the normal states but defined for the operations under unplanned contingency states, as denoted by the subscript C.

2.1.2. *The optimization problem*

A compact formulation for the deterministic outage planning problem is given as in (1):

$$\begin{aligned} \max\ J(\boldsymbol{X}) \\ \text{s.t:} \\ h_{\text{PM}}(\boldsymbol{X}) \leq 0, \\ h_{\text{capacity}}(\boldsymbol{X}) \leq 0, \\ h_{\text{balance}}(\boldsymbol{X}) = \boldsymbol{\zeta}, \\ h_c(\boldsymbol{X}) = 0, \forall c \in \mathcal{C} \end{aligned} \tag{1}$$

where $J(\boldsymbol{X})$ defines the objective function to maximize (more details in the next section), h_{PM} represents the constraints on the PM activities, h_{capacity} are the capacity constraints of network components, i.e., generators, line thermal limits, h_{balance} are nodal power balance constraints, and h_c are security constraints for all unplanned $c \in \mathcal{C}$.

For the sake of simplicity, the operations of the grid are modeled using a linear transmission model. In future extensions, DC power flow constraints or other power flow models will be included in the problem formulation.

2.1.3. *Objective function*

The det-SCOP problem optimizes a cost function that balances outage costs, load shedding costs weighted using the value of the lost load (VoLL), and operational generation costs, both under planned and unplanned contingency scenarios. This objective is formulated as in (2):

$$\begin{aligned} J(\boldsymbol{X}) = & \sum_{t,o} \frac{T-t}{T} \cdot x_{t,o} \cdot \rho_o \\ & - \text{VoLL} \cdot \sum_{t,b} \left(\zeta_{t,b} + \sum_{c} \zeta^c_{t,b,c} \right) \\ & - \sum_{t,g} w_g \cdot P_{t,g}, \end{aligned} \tag{2}$$

where ρ_o is a priority factor for outages based on their relative importance, $\zeta_{t,b}$, $\zeta^c_{t,b,c}$ are the load sheddings at time t and node b under normal conditions and unplanned contingency scenario c, respectively, and $P_{t,g}$ is the power generated by generator g at time t weighted by its generation cost w_g.

2.1.4. *PM constraints*

Let $h_{\text{PM}}(\mathbf{X}) \leq 0$ represent the set of PM constraints for all outages and all time steps. These constraints are defined $\forall t = 1, ..., n_t - 1$ and $\forall o$ to ensure consistent start and end indicators:

$$\begin{aligned} s_{t,o} &\leq s_{t+1,o}, \\ e_{t,o} &\leq e_{t+1,o}, \\ s_{t,o} &\leq e_{t+1,o}, \end{aligned}$$

Additionally, equality constraints on the PM tasks duration and number (linked to maintenance crew capacity) are imposed as follows:

$$\begin{aligned} s_{t,o} - e_{t,o} = x_{t,o}, &\quad \forall t, o \\ \sum_{o \in \mathcal{O}} x_{t,o} = m_t, &\quad \forall t \in \mathcal{T}, \\ \sum_{t \in \mathcal{T}} x_{t,o} = d_o, &\quad \forall o \in \mathcal{O}, \end{aligned}$$

where m_t is the maximum number of allowed PM tasks at time t, and d_o defines the expected duration of the maintenance activity o.

2.1.5. *Component state and capacity constraints*

To model the effect of the PM activities on the component's state, a binary variable $y_{t,\text{comp}}$ is defined for each element comp in the grid as follows:

$$y_{t,\text{comp}} = \begin{cases} 1 - x_{t,\text{comp}}, & \text{if comp} \in \mathcal{O}, \\ 1, & \text{otherwise.} \end{cases}$$

Note that $y_{t,\text{comp}} = 0$, only if the component comp belongs to the planned outage set and if a PM activity is scheduled at time t. The constraint h_{capacity} in program (1), comprises a set of generation and line capacity constraints under normal planned conditions. The generation capacity limits are imposed $\forall g \in \mathcal{G}$, $t \in \mathcal{T}$ as follows:

$$y_{t,g} P^{\min}_{t,g} \leq P_{t,g} \leq y_{t,g} P^{\max}_{t,g}, \tag{3}$$

where $P_{t,g} \in [P_g^{min}, P_g^{max}]$, or $P_{t,g} = 0$, if g undergoes maintenance at time t. Line capacity constraints $\forall l \in \mathcal{L}$, $t \in \mathcal{T}$ are also imposed as follows:

$$-y_{t,l} f_l^{\max} \leq f_{t,l} \leq y_{t,l} f_l^{\max}, \quad (4)$$

where $f_l^{\max}$, is the maximum flow allowed on line l, and $y_{t,l}$ forces $f_{t,l} = 0$ if $x_{t,l} = 1$.

2.1.6. *Power balance constraints*

Let $h_{\text{balance}}(\boldsymbol{X}) = \boldsymbol{\zeta}$ represent the traditional nodal balance constraints, defined for each node n as follows:

$$P_{t,n}^{\text{gen}} - P_{t,n}^{\text{d}} - \sum_{k \in \mathcal{N}} (f_{t,(k,n)} - f_{t,(n,k)}) = -\zeta_{t,n},$$

where $P_{t,n}^{gen}$ is the power generated at the node at time t, $P_{t,n}^{dem}$ is the power demand at time t, the summation term represents the net power inflow of lines connected to the node n, and $\zeta_{t,n}$ represents the demand-supply gap, i.e. the load shedding.

2.1.7. *Security constraints*

To ensure reliability under contingencies, N-1 security constraints are incorporated, ensuring that the system can operate safely even with the failure of a single component. These constraints adjust line flows and generator outputs under contingency scenarios $\mathcal{C}$. For this, we include a set of security constraints defined as $h_c(\boldsymbol{X}) \leq 0$, which include capacity constraints on the transmission lines and power balance equations for all $c \in \mathcal{C}$.

3. The proposed CVaR-SCOP formulation

The CVaR-SCOP formulation extends the deterministic SCOP by integrating a risk metric based on the concept of Conditional Value at Risk (CVaR) into the objective function to account for demand uncertainty and operational risk. By evaluating performance across S demand scenarios, the approach ensures robust solutions that minimize costs while penalizing demand-supply mismatches (load shedding). The CVaR component addresses the tail risks associated with extreme demand variations.

3.1. *Objective function*

The objective function incorporates the expected costs and the CVaR-based metric to penalize scenarios with significant load shedding. The CVaR threshold level, defined as $\zeta_{t,b}$ under normal operational conditions, is treated as a Value at Risk (VaR) level:

$$\min_{\boldsymbol{X},\boldsymbol{\eta},\zeta} J(\boldsymbol{X}) + \sum_{t,b} \left(\zeta_{t,b} + \frac{1}{\alpha N} \sum_{i=1}^{S} \eta_{t,b}^{(i)} \right),$$

$$\text{s.t. } \eta_{t,b}^{(i)} \geq \delta_{t,b}^{(i)} - \zeta_{t,b}, \quad \forall i = 1, \ldots, S, \ \forall t, b,$$

$$\eta_{t,b}^{(i)} \geq 0, \quad \forall i = 1, \ldots, S, \ \forall t, b.$$

Where $J(\boldsymbol{X})$ is the original objective function for a nominal demand scenario, $\zeta_{t,b}$ is the value-at-risk under nominal conditions, and $\eta_{t,b}^{(i)}$ are auxiliary variables that quantify excess costs beyond $\zeta_{t,b}$ for scenario i. The parameter $\alpha \in [0, 1]$ represents the risk aversion parameter, with lower values prioritizing risk aversion. Additionally, S denotes the number of demand scenarios. It is important to note that the constraints imposed on the original det-SCOP are also applied to this risk-averse formulation, but these are omitted here for the sake of simplicity. One should also note that, by defining the risk metric using the demand-supply gap $\zeta_{t,b}$ as a representation of the value-at-risk, we ensure that the risk is computed with respect to the nominal conditions. However, this approach does not allow for insights on the of the tail's actual probability mass. Drawbacks and benefits of this choice will be analyzed in future extensions.

3.2. *Demand uncertainty*

Demand uncertainty is represented by $P_{t,b}^{\text{d},(i)} \sim F_d$, where F_d is a probabilistic demand model for the load consumption at all nodes and planning time steps, assumed available for analysis sake. For each scenario with superscript (i), nodal balance equations are re-computed as follows:

$$P_{t,b}^{\text{gen}} - P_{t,b}^{\text{d},(i)} - \sum_{k \in \mathcal{N}} \left(f_{t,(k,b),n} - f_{t,(b,k),n} \right) = -\delta_{t,}^{(i}$$

where $\boldsymbol{\delta} \in \mathbb{R}^{+,n_B \times n_T \times N}$ represents the nodal supply-demand mismatch during contingencies.

4. Case study

The IEEE 24-RTS system is used to evaluate the proposed det-SCOP and CVaR-SCOP approaches under realistic operational conditions. The system comprises $n_L = 33$ transmission lines (plus 5 transformers). There are $n_G = 10$ generators and 17 non-zero load nodes, distributed over $n_B = 24$ buses. The hourly demand data for this test case are sourced from Subcommittee (1979), which is re-scaled by the selected step size of the planning horizon by taking the maximum load within the consecutive steps. The planning horizon consists of $n_t = 365$ daily time steps, corresponding to a one-year period.

Concerning the PM activities, the planned outage set denoted by $\mathcal{O}$ consists of $n_o = 8$ components: two generators and six transmission lines. The line indices considered are [0, 1, 2, 3, 5, 8], while the generator indices are [1, 2]. The expected duration of the PM activities varies significantly, ranging from 7 days to 60 days, with specific durations d_o set as [25, 7, 55, 7, 30, 30, 30, 60] (the last two terms are for the generators). Each PM activity is also assigned a priority score ρ_o, with values [1, 2, 1, 3, 2, 1, 1, 3], indicating that line 3 and generator 2 have the highest priority, followed by line 1 and line 5. The maximum number of simultaneous PM activities is set to $m_t = 2$ for all time steps.

The contingency set, $\mathcal{C}$, includes the first 30 $N-1$ single-line failures, ensuring robust schedules in the face of operational disruptions. To account for variability in demand, $S = 10$ load samples are generated for each node and time step and the value of lost load, representing the cost of demand-supply gaps, is set to 10^6 monetary units [m.u./MWh]. The generator costs are assumed stationary and set to a unitary cost ($w_g = 1$) for all generators.

This configuration provides a comprehensive basis for comparing the det-SCOP and the CVaR-SCOP approaches, emphasizing their effectiveness in managing maintenance scheduling while addressing risk sensitivity and operational constraints.

5. Results and comparison

This section presents a set of preliminary results that serve as an initial validation of the proposed approach. While these results are still in the early stages of analysis, they provide valuable insights into the effectiveness and potential of the methodology. It is important to emphasize that these findings, though preliminary, are important to establish a foundation for further investigation. In addition, they highlight the feasibility of the proposed approach and set the stage for more comprehensive evaluations in subsequent phases of the study.

5.1. *Outage schedule*

Figure 1 provides a side-by-side comparison of the schedules generated by the det-SCOP and CVaR-SCOP approaches for eight PM activities. The figure is divided into eight subpanels, each representing the binary variable $x_{t,o}$, which indicates whether a specific PM activity is scheduled at a given time. Solid lines represent the det-SCOP schedule, while dashed lines correspond to the CVaR-SCOP results, emphasizing the differences that arise from incorporating risk-awareness into the planning process.

It should be noted that the scheduling results for the PM activities differ between the two approaches. This divergence highlights the impact of considering risk through the proposed CVaR approach. However, the underlying reasons for these differences are not immediately apparent, and a more detailed analysis is necessary in order to provide better insight into how risk-awareness influences the scheduling decisions.

Future work will focus on extending this analysis by incorporating a more detailed examination of the risks and trade-offs associated with each approach. Such an investigation will shed light on the observed differences and provide more details on the advantages of the proposed CVaR-informed methodology.

5.2. *Line flows*

Figure 2 presents a comparison between the expected line flows for the first 15 lines using both the deterministic SCOP (det-SCOP) and CVaR-informed SCOP (CVar-SCOP) methods. The analysis of the line flows reveals how the inclusion of risk awareness in the CVaR-SCOP formulation influences the scheduling and flow distribution across the network. While the det-SCOP method tends to follow a more flat pattern, the CVar-SCOP method adjusts the flows to account for the uncertainties, resulting in a more variable flow pattern. This adjustment probably aims to mitigate the impact of potential high-cost scenarios, leading to a more resilient system.

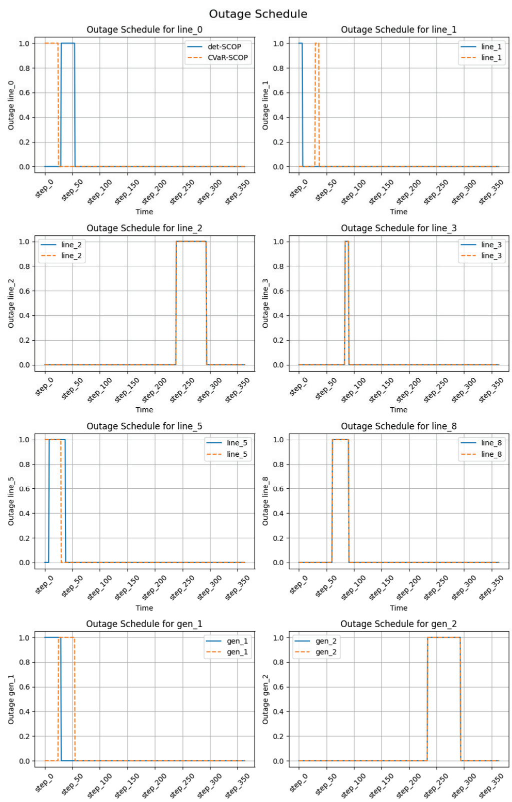

Fig. 1. A comparison between the 8 planned outages scheduled using det-SCOP and CVar-SCOP.

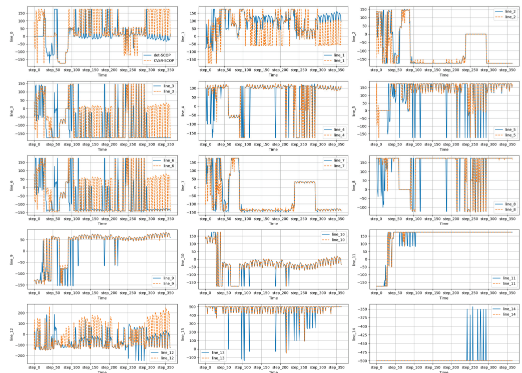

Fig. 2. A comparison between the expected line flows on the first 15 lines as for the det-SCOP and CVar-SCOP methods.

5.3. *Time-varying aggregated risk distribution*

Figure 3 illustrates the trend in the total CVaR-based metric over time, which is the sum of CVaR-based metric values over all nodes and time steps. As seen in the figure, the total risk closely follows the load profile, indicating that the highest risk occurs during periods of high demand. This correlation suggests that the system is more vulnerable during peak load periods, which underscores the importance of incorporating risk measures into the planning process to ensure reliability during these critical times.

5.4. *Nodal risk distribution*

Figures 4 and 5 present the risk distribution across the network nodes. The first figure shows the PDFs of the CVaR-based metric values for nine load busses at each time step. These densities illustrate how the risk is distributed across different parts of the network, with higher values indicating more significant risk exposure at certain load busses (the different magnitudes on the x-axis).

The second figure presents the empirical CDFs of CVaR-based metric values, aggregated over all nodes in the system. The CDFs provide insight into the overall risk exposure of the system as well as each node, helping to identify the nodes most susceptible to high-risk events. By comparing the two figures, we can observe the varying risk levels at different locations in the network, which are influenced by both the load patterns and the network's topological structure.

6. Discussion, conclusions, and prospects

This paper investigated deterministic security-constrained outage planning (SCOP) and CVaR-informed SCOP methods. We compared the two approaches and their resulting maintenance schedules using the IEEE 24 RTS system. The evaluation of risk distributions highlights how incorporating risk awareness enhances resilience in power system planning. The presented figures illustrate some of the key findings and their implications for future optimization and risk management in power systems. Specifically, the risk-informed approach has demonstrated its ability to provide solutions that account for risks and uncertainties by implementing a modified operational plan, such as adjusted outage scheduling and more flexible load flow profiles. While these preliminary results highlight the promising effect of a risk-informed approach, the extent of its effectiveness and robustness needs to be evaluated in more detail.

Future work will extend this research by incorporating power flow equations to better capture operational constraints, exploring trade-offs between risk reduction and maintenance costs, and developing advanced data generation methods to model uncertainties in demand, production, outage durations, and unplanned contingencies. Ad-

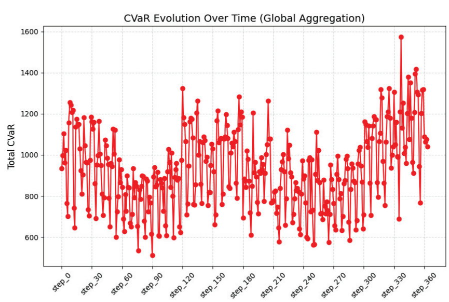

Fig. 3. Trend in the total CvaR-based metric over time (summation over all nodes for all time steps). One should note that it is correlated with the total load profile.

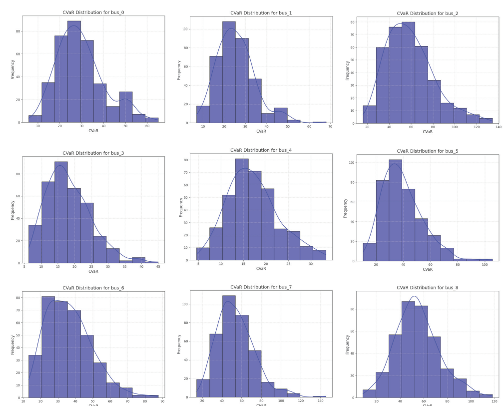

Fig. 4. Densities of CVaR values for $t \in T$ estimated from the samples on nine load busses.

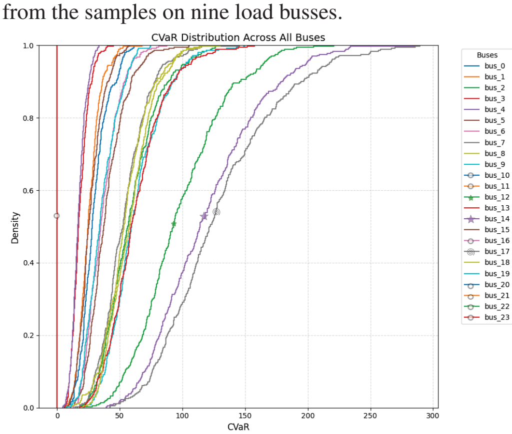

Fig. 5. Empirical CDFs of CVaR-based metric values for $t \in T$ estimated from the S samples on all busses.

ditionally, we will implement efficient numerical techniques to scale the framework for application to larger, national-level systems. These improvements aim to enhance the practicality and scalability of risk-aware power system optimization.

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