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Stochastic Sequential Restoration Planning with Risk Awareness and Ferroresonance Avoidance

Xianyi Yang[1]
E-mail: xianyi.yang@centralesupelec.fr

Alicia Bassière[1]
E-mail: alicia.bassiere@centralesupelec.fr

Jakob Puchinger[2,1]
E-mail: jpuchinger@em-normandie.fr

Adam Abdin[1]
E-mail: adam.abdin@centralesupelec.fr

Anne Barros[1]
E-mail: anne.barros@centralesupelec.fr

1. Université Paris-Saclay, CentraleSupélec, Laboratoire Génie Industriel, 91190, Gif-sur-Yvette, France.
2. EM Normandie Business School, Métis Lab, 92110 Clichy, France ;

Large-scale blackouts caused by extreme weather events pose critical challenges to modern power systems, disrupting essential services and causing severe economic and social losses. Conventional restoration strategies typically rely on predesigned backbone networks, assuming intact transmission infrastructure and stable operating conditions. However, storms and other extreme events frequently induce extensive physical damages to power system components, invalidating these assumptions and highlighting the need for more adaptive restoration approaches. This study develops a stochastic sequential optimization framework to model and improve post-storm power system restoration under uncertainty in failure probabilities arising from incomplete information about component health status. Using weather data, the failure probabilities of transmission lines are estimated and incorporated into a markov decision process (MDP) formulation. We consider uncertainty in line failure probabilities but assume that operators can update their estimation based on the latest available information as restoration progresses, which aligns with real-time situational awareness practices. The power grid is represented as a graph, where operators sequentially energize components to reestablish connectivity between substations. The model enforces critical operational and safety constraints, such as generation capacity limits, power flow constraints, and ferroresonance avoidance rules, often neglected in existing studies, to ensure both efficient and secure restoration. The proposed model enhances grid resilience by enabling adaptive restoration planning that dynamically responds to evolving system conditions. To the best of our knowledge, this is the first study to incorporate uncertain failure probability and ferroresonance avoidance explicitly into power system restoration modeling.

Keywords: risk-aware restoration, stochastic sequential optimization, markov decision process, storm-induced failures, resilience optimization.

1. Introduction

Storms can compromise power grid integrity and trigger large-scale blackouts with significant economic and security implications (Chou et al., 2013). Rapid system restoration is therefore considered essential for mitigating such impacts (Liu et al., 2016; Sun et al., 2018).

Following a major blackout, transmission system restoration generally proceeds through black-start, network reconfiguration, and load restoration (Liang et al., 2024). In practice, these stages frequently overlap due to the scale and severity of disruptions. During restoration, transmission line energization poses operational challenges, particularly related to voltage control and equipment security. To reduce risk, system operators typically energize lines sequentially and follow predefined backbone restoration plans based on operational experience, the one every each Transmission System Operators (TSO) has to prepare in advance and keep updated (European Network of Transmission System Operators for Electricity, 2015). However, extreme weather events can cause substantial infrastructure damage, leading to system conditions that diverge from those assumed in traditional procedures and complicating backbone restoration (El-Werfelli et al., 2009).

Prior work on power system restoration has explored optimization-based formulations (Sun et al., 2018), Monte Carlo tree search approaches (Wu et al., 2022), and Markov decision process based (MDP) decision support frameworks (Wu et al., 2024). Although these studies offer valuable methodological insights, most do not explicitly consider extreme weather impacts, limiting their applicability in extreme weather restoration scenarios.

One promising approach for addressing such impacts is to incorporate weather-induced transmission line failure probabilities into restoration planning. These probabilities are essential for reliability assessment (Yang et al., 2019) and have been used mainly in resilience-oriented studies, including outage modeling, risk analysis, and asset hardening (Panteli and Mancarella, 2015; Trakas and Hatziargyriou, 2019; Ma et al., 2022; Jalilpoor et al., 2022). Only limited work incorporates failure probabilities directly into restoration decision-making (Arpali et al., 2023). In such contexts, fragility models are commonly used to quantify component vulnerability (Dai and Preece, 2025), though substantial epistemic and data-driven uncertainties remain (Karagiannakis et al., 2025; Roueche et al., 2018). Empirical evidence shows that the failure probability of storm exposed transmission lines is intrinsically uncertain rather than deterministic. As demonstrated in Li et al. (2024), tower line systems subjected to identical wind speed may nonetheless exhibit markedly different fragility and failure behaviors due to variability in structural properties and environmental drivers, for example wind direction, gustiness, and icing. Epistemic uncertainty stemming from limited observations and modeling assumptions further contributes to dispersion in failure outcomes (Roueche et al., 2018). These findings imply that a deterministic failure probability does not capture the inherent variability induced by interacting physical factors.

In this paper, we formulate adaptive restoration as an MDP that supports sequential decision-making under uncertainty. The goal is to identify restoration paths that balance restoration time and operational risk, where time is linked to the number of energized lines (Sun et al., 2018) and risk reflects storm-induced line failure probabilities. Damage uncertainty is explicitly modeled and updated during restoration. Operational constraints, including generator capacity, power flow feasibility, and ferroresonance avoidance, are enforced throughout. Ferroresonance refers to a nonlinear oscillatory phenomenon arising from the interaction between transformer core saturation and network capacitances (Rezaei, 2022), typically triggered during the energization or de-energization of lightly loaded or unloaded transformers, potentially inducing hazardous overvoltages that compromise both equipment integrity and operational safety (Sabiha and Alkhammash, 2022); thus, it constitutes a critical phenomenon that must be explicitly accounted for. Computational experiments on the `Case6515rte` system, which reflects the scale and topology of the French very high voltage (HV) transmission system (Josz et al., 2016), demonstrate that the method yields restoration plans that are time-efficient and low-risk under realistic constraints. Our main contributions are:

(1) Incorporating line failure probabilities and their uncertainty into restoration decision making. The calculation is based on the fragility curve and weather data and the uncertainty is described by a distribution.

(2) Explicitly modeling operational ferroresonance avoidance constraints to enhance practical applicability.

(3) Formulating restoration as a MDP that is validated on the `Case6515rte` system.

2. Methodology

Setup The restoration process can be viewed as the progressive expansion of a tree rooted at backbone substations, where transmission lines and transformers are sequentially energized until the backbone is fully restored (Zhao and Wang, 2022). The central task is to determine an effective energization order for these components.

We represent the power system as a graph $G = (\mathcal{N}, \mathcal{F})$, where nodes $\mathcal{N}$ denote substations and edges $\mathcal{F}$ denote transmission lines or transformers. At time t, the system state S_t reflects the set of restored nodes, and the operator selects an action $a_t = (i, j)$ that energizes an edge connecting a restored node i to an unrecovered node j. The objective is to construct an energization sequence that minimizes restoration time while controlling operational risk.

Storm-induced risk are incorporated by assuming incomplete knowledge of line health following the disturbance. Failure probabilities of transmission lines are estimated from wind speed data and subsequently updated as restoration progresses based on field assessments.

High voltage (HV) line energization also entails physical constraints, particularly related to ferroresonance risks. To ensure operational feasibility, constraints are imposed on line length, transformer apparent power, and minimum load, with additional load requirements when these conditions cannot be satisfied.

Under these considerations, the restoration problem can be formulated as a MDP, as detailed in the following subsections.

State Space At time t, operator observes a state,

$$S_t = \big(\{ \delta_{f,t} \}_{f\in\mathcal{F}},\ \{p_{f,t}\}_{f\in\mathcal{F}} \big) \tag{1}$$

where $\delta_{f,t} \in \{0, 1\}$ indicates whether line f has been restored and $p_{f,t} \in [0, 1]$ denotes its current failure probability. From $\{\delta_{f,t}\}$, additional indicators are inferred, including the restored node set $\mathcal{N}_t^{Restored}$, remaining dispatchable generation g_t^{max}, served load demand d_t^{total}, cumulative restored HV line length L_t, and the pre-insertion load d_t^{pre} together with the post-insertion load d_t^{post}. These quantities guide feasible action selection and influence reward evaluation during restoration. They would be introduced in following parts, especially in transition function part.

Action Space At time t, the restored network contains nodes $\mathcal{N}_t^{restored} \subseteq \mathcal{N}$. The candidate action set,

$$\begin{aligned} \mathcal{A}(S_t) \ = \ \{ \, & f = (i,j) \in \mathcal{F} | i \in \mathcal{N}_t^{restored}, \\ & j \notin \mathcal{N}_t^{restored}, p_{f,t} \neq 1, \\ & g_t^{gen} - d_j^{load} \geq 0\} \end{aligned} \tag{2}$$

consists of lines or transformers that connect the restored network to an unrecovered node while respecting basic feasibility. Here, the failure probability of candidate component does not equal to 1. Furthermore, we have to ensure the load to be restored, d_j^{load} , can not exceed the remaining generation capacity. The operator then selects an action $a_t \in \mathcal{A}(S_t)$, i.e., energizes one new line or transformer. Two operational situations require modified action sets:

(a) HV line continuation. If the most recently restored component is a HV line $a_{t-1} = (m, n)$, the next action must continue from node n, $\mathcal{A}(S_t) = \{ f = (n, j) \in \mathcal{F}\}$. This reflects that HV energization primarily enables downstream restoration. The cumulative HV length L_t is updated until a transformer is reached.

(b) Minimum-load satisfaction after transformer energization. If a transformer is restored and L_t is below its admissible length threshold, subsequent actions must energize downstream load until a minimum amount (50 MW) is reached. Let $\mathcal{N}_t^{reach}$ contain nodes restored after the condition is triggered, which maintain a independent node subset from the general node set $\mathcal{N}_t^{restored}$. The admissible actions may only involve components connected to nodes in this subset. Once the load requirement is satisfied, $\mathcal{N}_t^{reach}$ resets.

Exogenous Information In practical applications, exogenous information is obtained from field sensors, crew inspections, or drone observations. This information is used to update the estimated failure probabilities of components awaiting restoration. During the training phase, operators only have access to probabilistic estimates of line failure risks. Thus, the failure probability of each candidate line is sampled from its corresponding distribution at each decision step.

Transition Function The transition function specifies how the state updates when action $a_t = f = (i,j)$ is taken. Restoring f activates node j, $\delta_{f,t+1} = 1$. Generation and load evolve as

$$d_{t+1}^{\max} = d_t^{\max} + \left(g_j^{\text{gen}} - d_j^{\text{load}}\right) \tag{3}$$

$$d_{t+1}^{total} = d_t^{total} + d_j^{load} \tag{4}$$

Ferroresonance avoidance constraints remain active until d_t^{total} exceeds 200 MW. While active, additional indicators regulate admissible energization sequences:

Cumulative HV length. If f is a HV line, $Voltage \geq 380KV$, length accumulates; otherwise it resets:

$$L_{t+1} = \begin{cases} L_t + L_f, & \text{if HV line} \\ 0, & otherwise \end{cases} \tag{5}$$

Pre-insertion load. If the length of restored lines is too long, L_t, or the apparent power of the restored transformer after the line, AP_f , is too large, operators must restore sufficient pre-insertion loads before proceeding:

$$d_{t+1}^{pre} = \begin{cases} 0, & \text{if required} \\ d_t^{pre} + d_j^{load} & \text{otherwise} \end{cases} \tag{6}$$

This equation implies that load is accumulated under normal conditions and reset to zero whenever a pre-insertion requirement is triggered and satisfied. The trigger thresholds are summarized in Table 1.

Table 1. Operational thresholds for triggering pre-insertion load

Type	Length (Km)	Apparent power(MVA)
Autotransformer	90	600
Others	45	240

Post-insertion load. When both L_t and AP_f remain below their respective thresholds, a transformer is considered restored under safe conditions. In this case, at least 50 MW of post-insertion load must subsequently be restored:

$$d_{t+1}^{post} = \begin{cases} d_t^{post} + d_j^{load} & \text{if safe condition} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

To track the temporary region associated with this requirement, a temporary restored set $\mathcal{N}_t^{reach}$ is maintained. This set is updated while the post-insertion requirement is active and cleared once the requirement has been fulfilled.

Model Uncertainty To represent the damage uncertainty, the exact failure probability p_f associated with line f is not known with certainty, as operators have limited situational information during the restoration process. The failure probability assessment will evolve based on updated information, and this characterization will be addressed in future work. In the experiments presented here, however, the failure probability is assumed to be deterministic and is assigned a fixed value.

Instant Reward As stated earlier, the goal is to energize substations along a predefined backbone path. At each time step, action $a_t = (i,j)$ yields a positive reward $R_b = r_b$ if node j belongs to the backbone set $\mathcal{N}^{\text{backbone}}$, and a penalty otherwise. Using a non-backbone action is penalized because it diverts limited restoration resources. To reflect the operational value of serving substantial loads, the penalty associated with non-backbone actions, R_{nb} , is defined to decrease with the magnitude of the restored load. In this formulation, penalties vanish once the restored load exceeds 50 MW, consistent with empirical observations that such load pickups seldom violate restoration constraints. The penalty term is given by

$$R_{nb} = r_{nb} \frac{(50 - d_j^{load})}{50}, \tag{8}$$

with $r_{nb} < 0$.

In addition, an extra penalty tracks the operational risk induced by energizing components with failure probability. This risk term is specified as

$$R_s = r_s p_{i,j,t}, \tag{9}$$

where $r_s < 0$ and $p_{i,j,t}$ denotes the current failure probability estimate of component $f = (i,j)$. The coefficients r_b, r_{nb}, and r_s are tuning parameters and should be selected to balance time efficiency and risk mitigation.

Objective Let μ be a stochastic policy that maps each state S_t to a distribution over actions a_t. Then the optimal policy is

$$\mu^* = \arg\max_{\mu} \mathbb{E}^{\mu}\Big[\sum_{t=0}^{T} R(S_t, a_t) \;\Big|\; S_0\Big]. \quad (10)$$

Here, $\mathbb{E}^{\mu}[\cdot \mid S_0]$ denotes expectation when actions are sampled from policy μ, $R(S_t, a_t)$ is the immediate reward received at time t, and T is the finite decision horizon. The initial state S_0 is defined by

$$S_0 = \big(\,\{\,\delta_{f,0} = 0\}_{\forall f},\ \{p_{f,0}\}\big) \quad (11)$$

indicating that no components are restored at the start.

Constraints *Generation Capacity* Operator actions must respect remaining generation capacity, so a candidate component $f = (n, j)$ is admissible only if

$$g_t^{gen} - d_j^{load} \geq 0 \quad (12)$$

Ferroresonance avoidance Compliance with ferroresonance avoidance rules is enforced by identifying violation conditions. A violation occurs if, after restoring a transformer under safe conditions, the cumulative post insertion load fails to reach the required threshold,

$$\mathcal{A}(S_t) = \emptyset \wedge d_t^{post} < 50 \quad (13)$$

A violation also occurs if a pre insertion load is required but cannot satisfy the minimum condition,

$$d_t^{pre} < 0.1AP_f \quad (14)$$

In addition, a violation is triggered if high voltage restoration reaches a dead end without a feasible successor. Whenever a violation occurs, the corresponding state is designated as infeasible and the action leading to that state is removed from the candidate action space.

Power flow Feasibility of power flow must also be maintained. If the loading percentage of any restored line exceeds its thermal rating, the state violates power flow constraints. Formally,

$$\frac{|F_{f,t}|}{F_f^{\max}} \leq 1 \quad (15)$$

where $F_{f,t}$ is the active power flow on line f at time t and $F_f^{\max}$ is its capacity. Power flow calculations are performed using the classical Newton Raphson method (da Costa et al., 1999). Reactive power follows analogous constraints and is therefore omitted for brevity.

The constraints are evaluated when constructing the candidate action set. Any action whose resulting state violates the constraints is removed from the candidate action set.

3. Case Study

Dataset The `case6515rte` dataset is used to evaluate the proposed restoration method. This case reflects the scale and topology of the French very high voltage (HV) transmission system (Josz et al., 2016), but lacks explicit line-length data, which is essential for restoration sequencing. To address this, line lengths are inferred from terminal bus coordinates. The aggregated HV line length obtained from coordinate interpolation (94,516 km) significantly exceeds the approximately 22,000 km reported by the French TSO (RTE France, 2019), due to distortions in the dataset's positional data. All inferred lengths are therefore scaled down to reconcile with realistic system dimensions.

Since large-scale national blackouts are rare and restorations proceed regionally, a representative subnetwork is extracted from the dataset as the target system. It contains 87 substations (in the dataset, also called buses), 34 lines at 380 kV, 38 lines at lower voltage, and 24 transformers.

Basic experiment In the baseline experiment, we set up a deterministic scenario to validate the model's feasibility, where the initial backbone bus is 6294, and the objective is to energize intermediate components until reaching the downstream backbone bus 6335. These two buses are set as backbone substation because their generation capacities are above 800 MW, reflecting the typical presence of large nuclear units in backbone infrastructure. All component failure probabilities are set to zero, resulting in a deterministic restoration problem that we can generate the optimal policy by applying Bellman operator via backward induction, which guarantees a globally optimal policy with rigorous convergence properties. In contrast, heuristic or approximate methods typically provide computationally efficient but suboptimal approximations.

The resulting restoration trajectory is shown in Fig. 1 and the details are shown in Table. 2. The path departs from bus 6294 through buses 670 and 4466, which form the only feasible outbound route. From bus 4466, the algorithm selects line 4466–958 as it leads directly toward the target backbone through line 958–1218. At this point, the cumulative energized HV length reaches 59.2 KM; directly energizing line 958–1218 would exceed the HV-length limit (119.7 KM), so a load pickup operation is required. The 958–957 autotransformer (542.3 MVA) is energized and subsequently supplies 56.40 MW via line 957–4637, satisfying the minimum load requirement. Restoration then proceeds through lines 958–1218 and 1218–1299, and finally transformer 1299–6335, completing backbone reconnection.

This experiment demonstrates that the obtained path satisfies topological and operational constraints (e.g., avoidance of ferroresonance) while maintaining a short sequence of restoration actions.

Failure probability experiment A second scenario introduces failure risk by assigning fixed probabilities of 80% to line 4466–958 and 10% to line 4466–1002, with all other parameters unchanged. The resulting sequence in Fig. 2 detours around the high risk line 4466–958 and instead energizes line 4466–1002 and its downstream components. This experiment demonstrates that the proposed algorithm effectively accounts for failure risk and avoids highly risky components during the restoration process.

Discussion These two experiments confirm that the proposed MDP-based restoration method can efficiently derive an energization sequence that satisfies the system's operational limits while minimizing the total number of restoration actions, avoiding high risky components and maintaining network stability.

4. Conclusion and discussion

This paper develops a risk-aware sequential restoration framework that incorporates storm-induced line failure probability and its uncertainty into an MDP formulation, allowing restoration decisions to reflect both estimated risk levels and confidence in those estimates. By integrating a risk-penalized reward design with ferroresonance-avoidance and power flow constraints, the proposed MDP-based approach produces feasible backbone connection paths that steer away from high-risk components while respecting practical operational constraints. These contributions highlight the importance of explicitly modeling uncertain failure probability in post-storm system restoration.

Future work will extend the analysis to stochastic scenarios in order to highlight the importance

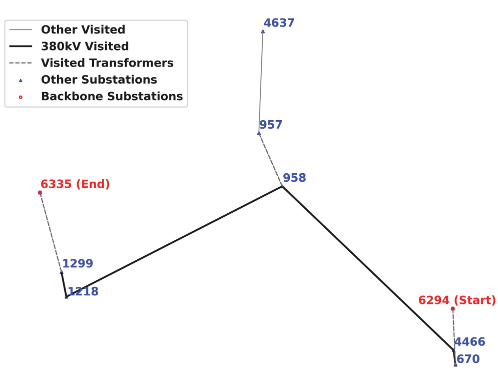

Fig. 1. Restoration path in basic experiment

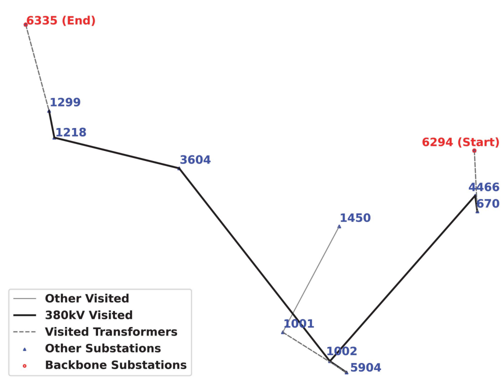

Fig. 2. Restoration path in failure probability experiment

Table 2. Detailed results in basic experiment

Step	**Action**	**Voltage (KV)**	d_t^{total} **(MW)**	L_t **(KM)**	AP_f **(MVA)**	d_t^{pre} **(MW)**	d_t^{post} **(MW)**
1	(6294, 670)	$24 \rightarrow 380$	0	0	–	0	0
2	(670, 4466)	380	0	3.7	–	0	0
3	(4466, 958)	380	0	59.2	–	0	0
4	(958, 957)	$380 \rightarrow 63$	0	Reset	542.3	0	0
5	(957, 4637)	63	56.4	0	–	56.4	56.4
6	(958, 1218)	380	56.4	60.5	–	56.4	Reset
7	(1218, 1299)	380	56.4	66.8	–	56.4	0
8	(1299, 6335)	$380 \rightarrow 24$	56.4	Reset	564	56.4	0

Note: The arrow notation in the "Voltage (kV)" column indicates the change in operating voltage level before and after the execution of the corresponding action.

of explicitly modeling damage uncertainty and to investigate system-level implications for larger-scale networks. As the network size increases and damage uncertainty is incorporated, the associated computational complexity grows substantially. To address this challenge, we intend to employ approximate dynamic programming (ADP), in which the Bellman recursion is approximated without the need to enumerate all possible future realizations of uncertainty. Compared with heuristic and metaheuristic approaches, ADP preserves the convergence and optimality properties of dynamic programming, which are generally difficult to guarantee in heuristic methods. In addition, ADP is expected to provide improved solution quality together with greater computational efficiency. Accordingly, future research will include a comparative evaluation with representative heuristic methods reported in the literature in order to assess the advantages of the proposed ADP approach in terms of solution optimality and computational time.

Beyond algorithmic extensions, the present study establishes a foundational modeling framework that can be further developed in several directions. For example, future models may incorporate explicit risk measures, economic considerations, and more detailed repair time dynamics. The framework can also support future studies that investigate the operational and planning impacts associated with the integration of renewable energy sources (RES), thereby contributing to more comprehensive resilience oriented decision support for modern power systems.

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