Quantifying Vegetation Risk and Cost-Effective Mitigation For Improved Distribution Resilience

Umar Salman, *Student Member, IEEE*, Zongjie Wang*, *Senior member, IEEE*

***Abstract*—Vegetation encroachment on distribution lines is a major cause of outages and a significant operations and maintenance expense, yet many utilities still rely on cyclical trimming that ignores span-level differences in vegetation risk. This mismatch leads to costly interventions that do not always deliver proportional reliability benefits. To address this challenge, this paper proposes a risk-based cost optimization framework that combines probabilistic tree-level risk assessment, span-level aggregation, and strategy-specific cost models to compare Complete Vegetation Clearing, Selective Tree Removal, and Targeted High-Risk Removal. Simulation studies on 600 scenarios across 36 spans of a real distribution circuit show that the Targeted High-Risk Removal strategy achieves the highest average Benefit–Cost Ratio (1.94), an average risk reduction of 22%, and a 13.7% reduction in total system impact, demonstrating that risk-prioritized, data-driven vegetation management can substantially improve both economic efficiency and distribution system resilience.**

***Index Terms*—Vegetation management, cost optimization, risk assessment, distribution systems, tree removal impact, benefit-cost ratio, infrastructure resilience**

I. Introduction

Vegetation-related outages continue to pose a significant challenge for electric distribution systems, often resulting in service interruptions, safety hazards, and high restoration expenditures. Utilities typically devote 10–15% of their annual operations and maintenance budgets to vegetation management [1], and these costs continue to rise with increasing storm severity, aging infrastructure, and expanding vegetation encroachment [2]–[4]. As a result, improving the efficiency and reliability impact of vegetation management remains a critical priority for utilities.

However, traditional vegetation programs largely rely on fixed trimming cycles and uniform clearance rules, approaches that overlook the substantial heterogeneity of tree-related risks across distribution spans. Factors such as species, tree health, conductor proximity, wind exposure, and downstream asset criticality contribute to widely varying risk levels, yet most existing practices do not incorporate this variability into decision-making. Consequently, utilities may overspend on low-risk spans while leaving high-risk locations insufficiently mitigated.

Prior research has explored reliability-centered maintenance, storm-driven risk modeling, economic assessments, and predictive analytics to support vegetation management decisions [4]–[7]. These studies have improved the understanding of failure mechanisms and the economic burden of vegetation-related outages.However, several gaps remain: (i) many models [5], [6] do not integrate tree-level probabilistic risk into span-level decisions; (ii) most studies [1], [4] evaluate a single vegetation strategy rather than comparing multiple approaches under a unified economic framework; and (iii) few works [5], [7] combine risk metrics, cost structures, and benefit-cost evaluation into a comprehensive optimization model suitable for operational planning. To address these challenges, this paper proposes a risk-based cost optimization framework that integrates probabilistic tree failure assessment, span-level risk aggregation, and strategy-specific cost modeling to evaluate multiple vegetation management strategies, complete vegetation clearing (CVC), selective tree removal (STR), and targeted high-risk removal (THR). The framework computes risk reduction benefits, strategy costs, and benefit–cost ratios (BCR) under diverse operational and economic conditions to identify the most efficient approach.

The main contributions of this paper are as follows:

- A unified cost optimization model that integrates tree-level risk probabilities, span-level risk aggregation, and strategy-specific economic components;
- Comparative evaluation of three vegetation management strategies, enabling utilities to quantify trade-offs in cost, risk reduction, and investment efficiency;
- A multi-criteria decision support metric combining BCR, risk reduction, cost-effectiveness, and target achievement for operational prioritization;
- Extensive simulation across 600 scenarios and 36 spans, demonstrating that targeted high-risk removal delivers the highest economic value, with BCR up to 1.94 and a 13.7% reduction in total system impact.

The remainder of this paper is organized as follows. Section II presents the problem formulation and cost optimization model. Section III describes the case study and data. Section IV provides simulation results and comparative analysis. Section V discusses implementation considerations, and Section VI concludes the paper.

II. Problem Formulation

The section describes the modeling frameworks and some of the key terms introduced for the purpose of the formulating the proposed cost optimization model.

U. Salman is with the Department of Electrical and Computer Engineering at the University of Connecticut, Storrs, CT, USA 06268. Z. Wang is with the Department of Electrical and Computer Engineering at Colorado State University, Fort Collins, CO, USA 80523. (*Corresponding author: Dr. Zongjie Wang, zongjie.wang@colostate.edu).

979-8-3315-8138-1

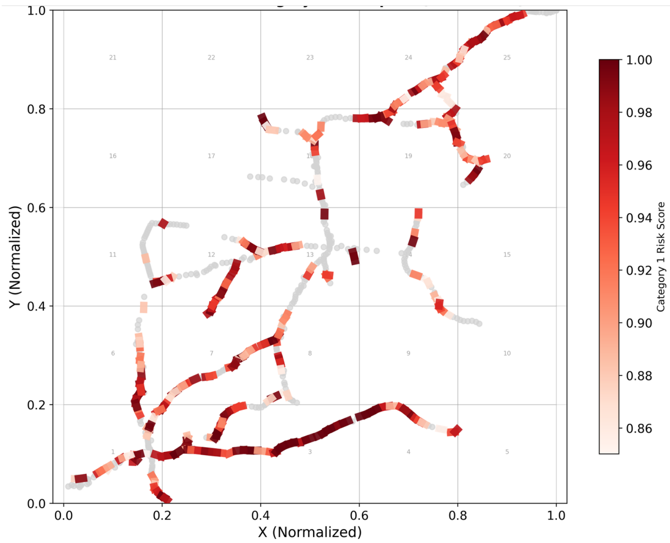

Fig. 1: Layout topology of the studied circuit.

A. *Risk Assessment Model*

The vegetation management optimization problem begins with quantifying the risk posed by individual trees to the distribution infrastructure. For each tree t in the system, we define the annual risk probability in (1).

$$R_t = P_{\text{failure}}(t) \times P_{\text{contact}}(t|f) \times I_{\text{impact}}(t), \tag{1}$$

where $P_{\text{failure}}(t)$ represents the probability of tree failure, $P_{\text{contact}}(t|f)$ is the conditional probability of conductor contact given failure [4], [8], and $I_{\text{impact}}(t)$ quantifies the impact severity, (2). represents the consequences of tree-caused outages and captures both the spatial extent of potential outages and the economic consequences measured in dollars.

$$I_{impact} \sum_{p \in P} W_p \cdot N_{cust,p} \cdot VOLL, \tag{2}$$

where W_p is the weighting factor for pole based on asset (transformer, lateral feeder, re-closer, switch, etc) criticality, $Ncust, p$ is the number of customers served downstream of pole p and VOLL is the value of loss of load [3].

The span-level risk aggregation is then defined. For each span s containing a set of trees T_s, the aggregate risk is calculated using (3):

$$R_s = 1 - \prod_{t \in T_s} (1 - R_t). \tag{3}$$

(2) accounts for the cumulative effect of multiple tree risks within a single span while avoiding double-counting of overlapping risk zones. Note that (1) and (3) only for selected trees with higher risks and with potential contact with circuit as expressed by the conditional component in (1) and thus preventing multiplicative product to zero.

B. *Tree-Infrastructure Impact Mapping*

The mapping between trees and potentially affected infrastructure is defined through (4):

$$\begin{aligned} P_t = \{p \in P \mid d(t,p) \leq H_t \\ \text{or } p \in S_w \text{ for some } w \in W_t\}, \end{aligned} \tag{4}$$

where P is the set of all poles in the system, $d(t,p)$ represents the Euclidean distance between tree t and pole p, H_t is the effective fall height of tree t, W_t denotes the set of conductors within the strike zone, and S_w represents poles supporting conductor.

C. *Cost Optimization Framework*

The vegetation management cost optimization problem is formulated in (5)-(8).

$$\min_{x_{ts}} \sum_{s \in S} \sum_{t \in T_s} C_{ts} \cdot x_{ts}, \tag{5}$$

$$\text{s.t.} \quad R_s^{\text{final}} \leq R_{\text{target}} \quad \forall s \in S, \tag{6}$$

$$\sum_{t \in T_s} x_{ts} \leq |T_s| \quad \forall s \in S, \tag{7}$$

$$x_{ts} \in \{0,1\} \quad \forall t, s, \tag{8}$$

where x_{ts} is a binary decision variable indicating whether tree t in span s is removed, and C_{ts} represents the total cost of removing tree t from span s. Equation (6) ensures that post-mitigation risk (R_s^{final}) is always less or equal to the targeted risk threshold desired.

D. *Strategy-Specific Cost Models*

Three distinct vegetation management strategies are considered, each with unique cost structures:

1) Complete vegetation clearing (CVC): The total cost for complete clearing is (9).

$$C^{\text{CVC}}_{mob} = C_{\text{mob}} + \sum_{t \in T_s} (C^{CVC}_{\text{tree}} + C_{\text{disp}}) + C_{\text{permit}}, \tag{9}$$

where C^{CVC}_{mob} is mobilization cost, C^{CVC}_{tree} is tree removal cost, C_{disp} is the tree disposal cost and C_{permit} is the cost associated with permit.

2) Selective tree removal (STR): For selective removal, the cost includes assessment overhead:

$$C^{\text{STR}}_{mob} = C_{\text{mob}} + C_{\text{assess}} + \sum_{t \in T_{\text{selected}}} (C^{\text{sel,STR}}_{\text{tree}} + C_{\text{disp}}) \tag{10}$$

3) Targeted high-risk removal (THR): The targeted approach incorporates risk-weighted prioritization (11).

$$C^{\text{THR}}_{mob]} = C_{\text{mob}} + C_{\text{risk}} + \sum_{t \in T_{\text{high}}} (C^{\text{targ}}_{\text{tree, THR}} + C^{\text{haz}}_{\text{disp}}), \tag{11}$$

where C_{STR} is selective tree removal cost, C_{assess} is assess cost, and C^{sel}_{tree} cost of selected trees, C^{targ}_{tree} is the unit cost for targeted high-risk tree removal and C^{haz}_{disp} is the disposal cost for hazardous tree material. The values of these parameters are given in Table II.

979-8-3315-8138-1

E. Benefit-Cost Ratio Analysis

The economic viability of each strategy is evaluated using the Benefit-Cost Ratio (12).

$$\mathrm{BCR} = \frac{\sum_{i=1}^{n} \frac{B_i}{(1+r)^i}}{\sum_{i=1}^{n} \frac{C_i}{(1+r)^i}}, \tag{12}$$

where B_i represents the benefits in year i, C_i represents the costs in year i, r is the discount rate, and n is the analysis period.

The final optimization considers multiple objectives through a weighted scoring function (13).

$$S = \alpha \cdot \mathrm{BCR} + \beta \cdot \Delta R + \gamma \cdot \frac{1}{C_{\text{total}}} + \delta \cdot \mathrm{NPV}, \tag{13}$$

where $\alpha, \beta, \gamma, \delta$ are weighting factors (with $\alpha+\beta+\gamma+\delta = 1$) in multi-criteria scoring. Other parameters described in Tables II–IV.

F. Performance Metrics

The effectiveness of each strategy is evaluated using:

$$\eta = \frac{\Delta R}{C_{\text{total}}} \times \mathrm{BCR} \times T_{\text{achieved}}, \tag{14}$$

where ΔR is the risk reduction, and T_{achieved} is a binary indicator for target achievement.

G. Temporal Analysis

The payback period analysis reveals important economic insights:

$$T_{\text{payback}} = \frac{\ln\left(\frac{C_0}{A\cdot(1-e^{-r})}\right)}{\ln(1+r)}, \tag{15}$$

where C_0 is the initial investment and A is the annual benefit.

III. Case Study and Methodology

The case study encompasses a distribution network consisting of 36 spans out of a total 330 spans with varying risk profiles and vegetation densities. The circuit topological layout is shown Fig. 1 showing the top risk spans in the selected area of the circuit. For privacy concern the detail of the network location and actual parametric profile is not disclosed but the circuit represents an actual distribution in Massachusett in United States. Each of the 36 spans in the circuit has an average span lengths of 250 meters, and 10 downstream nodes. Furthermore, the number of high-risk trees identified include 312, average tree per span of 8.9 and species diversity index is assumed as 0.67. Tables II–I provides parameters assumed for the simulation in this study [3], [9].

TABLE I: Economic Parameters for Financial Analysis.

Parameter	Value
Analysis period	15 years
Discount rate	5%
Inflation rate	3%
Labor cost escalation	4% annually

TABLE II: Cost Parameters by Strategy (USD).

Parameter	CVC	STR	THR
Cost per tree	250	350	450
Mobilization	800	500	600
Equipment daily	1,200	800	900
Crew daily	1,500	1,200	1,400
Permit cost	300	150	200
Disposal per tree	50	75	85

IV. Simulation Results and Analysis

Across 600 Monte Carlo scenarios and 36 spans, the model reveals consistent trade-offs among the three strategies. The number of scenarios was selected based on computational tractability while ensuring adequate sampling of the parameter space. Key randomized parameters include tree failure probability; cost parameters varied around Table II values and customer impact factors. Fig. 2 summarizes core performance patterns: the left figure shows that average total cost rises with the number of trees removed, with CVC tracking the highest outlay, STR the lowest, and THR in between; the middle figure indicates that both STR and THR sustain BCR above unity across most tree-count settings; and the right figure demonstrates a monotonic relationship between cost and risk reduction, with THR delivering the steepest marginal risk reduction for a given spend. These figure-level trends align with the aggregate metrics in Table III, where the mean BCR over all scenarios is 1.78, average cost per scenario is $15,304, and target risk thresholds are satisfied in every case. At the portfolio level, the simulation indicates a 13.7% reduction in overall impact (24.7 units in absolute terms), with an average risk reduction of 15.4% and 84.2% of scenarios yielding BCR > 1.

A. Strategy Comparison

The comparative metrics in Table IV reinforce the qualitative signals in Fig. 2. CVC achieves the highest absolute risk reduction (21.0%) but produces the lowest cost-effectiveness (BCR = 1.49), reflecting its higher mobilization, crew, and equipment intensities. STR offers a balanced economic profile (BCR = 1.90) while preserving substantial risk reduction (20.0%), making it attractive for circuits where span-by-span selectivity is feasible. THR attains the best overall performance (BCR = 1.94) and the largest risk reduction (22.0%) by concentrating removals in spans that drive system risk, consistent with the risk-weighted cost structure in Table II. Fig. 3 further illuminates these contrasts: the left figure scales multiple metrics for a direct side-by-side view (cost, BCR, risk reduction, and NPV), the middle figure shows that unit

979-8-3315-8138-1

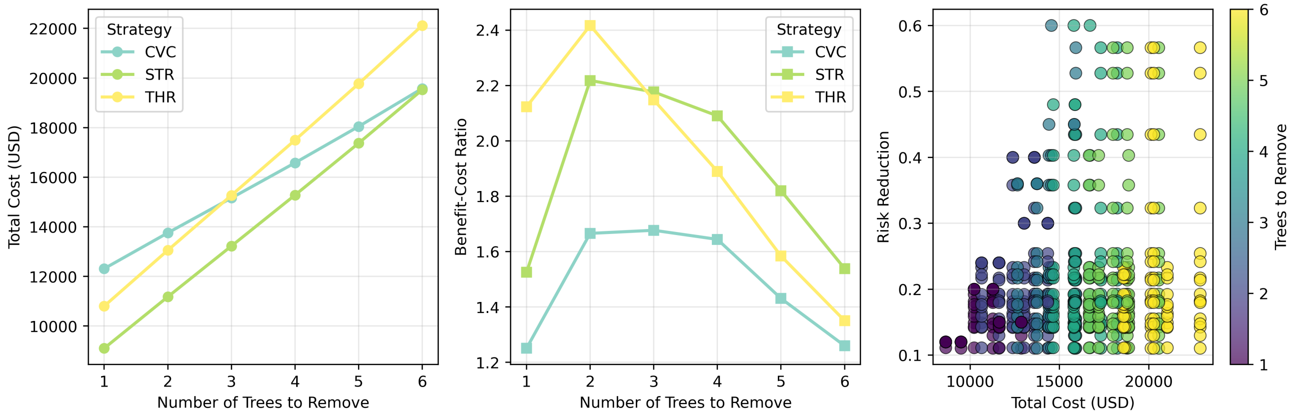

Fig. 2: Average cost (left), BCR (middle) Comparison across strategies .and Cost-Risk reduction (Right).

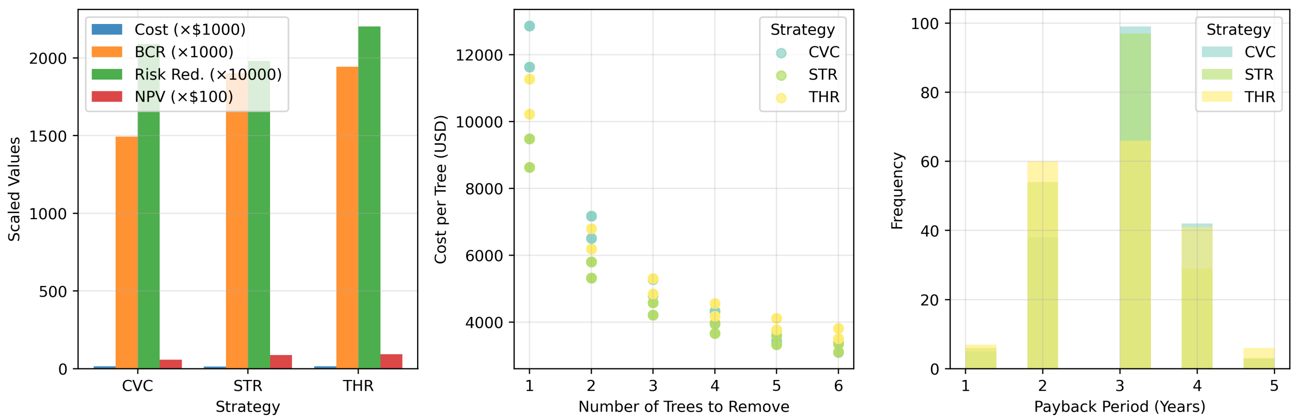

Fig. 3: Strategy comparison (left), Cost per tree per strategy (middle) Payback period distribution (Right).

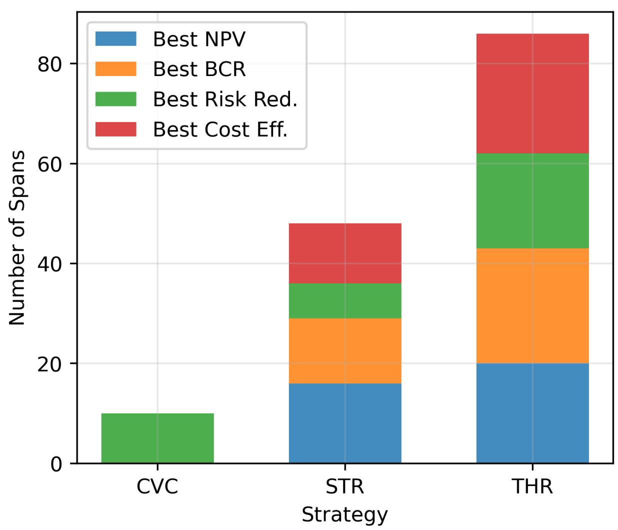

Fig. 4: Optimal strategy by criteria based on CVC (left), STR (middle) and THR (Right).

TABLE III: Simulation Performance.

Metric	Value
Total scenarios analyzed	600
Spans analyzed	36
Average cost per scenario	\$15,304
Average BCR	1.78
Profitable scenarios ($BCR > 1$)	505 (84.2%)
Average risk reduction	15.4%
Total impact reduction	24.7 units
Impact reduction percentage	13.7%
Target achievement rate	100%

TABLE IV: Comparison of Vegetation Management Strategies.

Metric	CVC	STR	THR
Average cost (\$)	15,733	14,031	16,149
Average BCR	1.49	1.90	1.94
Risk reduction (%)	21.0	20.0	22.0

costs remain stable as tree count increases when strategies are matched to risk, and the right figure displays payback realizations clustering in the 3–4 year range.

B. *Span-Level and Downstream Effects*

Span-level heterogeneity is material to planning. Table V lists the top five spans by impact reduction; these spans combine above-average tree counts (5–8 trees) with elevated pre-mitigation risk, so targeted interventions yield outsized

979-8-3315-8138-1

TABLE V: Top 5 Spans by Impact Reduction.

Span ID	Impact	Risk Δ	Trees
13318454	5.6	0.177	8
13318555	5.0	0.155	7
13318221	4.8	0.149	5
13318247	4.7	0.147	7
13318222	4.6	0.143	5

TABLE VI: Downstream Components Affected.

Component	Count	Impact Weight
Spans	5	1.0
Nodes	10	0.8
Transformers	5	1.2
Fuses	5	0.6
Customers	50	0.2

benefits. The downstream component map in Table VI indicates that, within the study footprint, five spans and ten nodes are directly implicated alongside five transformers and five fuses, with fifty customers potentially affected. This mapping matters operationally: reductions achieved on high-leverage spans propagate to downstream elements with weights that reflect both exposure and consequence, amplifying the value of precise targeting.

C. Benefit–Cost Ratio Distribution and Payback

The distribution in Fig. 4 confirms that the right tail of BCR is dominated by THR, with instances exceeding 6 under favorable combinations of risk gradient and tree mix. One notable example is span 13318814, where a three-tree intervention produced a BCR of 6.37, a 56.6% risk reduction, and a total cost of $15,916—an illustration of how risk-weighted prioritization can unlock substantial value when the marginal removal set aligns with hazard drivers. Payback performance is consistent with these findings: average payback is approximately 3.8 years for CVC, 3.2 years for STR, and 2.9 years for THR, highlighting that focused, risk-driven actions recover investment more quickly while still achieving target compliance.

V. Discussion and Implementation Considerations

Collectively, Fig. 2–Fig. 4 and Tables II–VI support three implementation insights. First, resource allocation benefits from a targeted paradigm: where span risk is concentrated, THR consistently converts limited budgets into larger risk decrements and higher BCR, thereby improving the efficiency of capital and crew time. Second, the span ranking endemic to the framework can be integrated with scheduling to sequence crews along high-impact corridors, smoothing mobilization and reducing equipment idle time; the "best by criterion" view in Fig. 4 shows how recommendations coalesce around THR under multiple economic lenses, while still identifying instances where STR is preferable. Third, the structure of the evidence, explicit risk reduction, documented target achievement, and traceable cost components, aligns with regulatory expectations for demonstrable reliability improvements and enables multi-year budget planning using Table III metrics as anchors.

VI. Conclusion

This paper demonstrates that a risk-based, cost-optimized framework can significantly enhance both the economic and reliability outcomes of utility vegetation management. Across 600 scenarios, strategic tree removal reduces total system impact by 13.7%, achieves all risk targets, and maintains an average scenario cost of $15,304, with 84.2% of cases yielding a Benefit–Cost Ratio above one. Among the evaluated strategies, Targeted High-Risk Removal achieves the strongest overall performance, producing a BCR of 1.94, an average risk reduction of 22%, and a payback period of approximately three years by concentrating efforts on spans with the highest hazard contributions. The 22% risk reduction achieved by THR directly translates to resilience improvement by lowering the conditional probability of widespread outages during extreme events, complementing existing reliability programs that primarily address routine failures under normal conditions.Selective Tree Removal emerges as an effective second option when span-specific assessments are feasible, while Complete Vegetation Clearing remains suitable for spans where uniform hazards or access limitations reduce the value of targeted actions. By integrating span-level risk analytics with explicit cost models and multi-criteria scoring, the proposed framework offers a rigorous foundation for investment planning, regulatory justification, and operational prioritization, with opportunities for future enhancement through climate- and learning-informed updates.

References

[1] J. Smith and A. Johnson, "Vegetation management in electric utilities: Current practices and future trends," *IEEE Transactions on Power Delivery*, vol. 35, no. 2, pp. 812–823, 2020.

[2] T. Liu, Z. Qi, A. Scaglione, J. P. Montoya-Rincon, J. Woodcock, J. E. Gonzalez-Cruz, M. Acquah, U. Salman, Z. Wang, and G. Itzstein, "Tree-induced power outage risk assessment and mitigation using lidar point clouds," in *2025 57th North American Power Symposium (NAPS)*. IEEE, 2025, pp. 1–6.

[3] D. Zhao, U. Salman, and Z. Wang, "Risk assessment of distribution networks considering climate change and vegetation management impacts," *arXiv preprint arXiv:2503.09239*, 2025.

[4] U. T. Salman, Z. Wang, and T. M. Hansen, "Power system resilience metrics based on tree failure model," in *2024 56th North American Power Symposium (NAPS)*. IEEE, 2024, pp. 1–6.

[5] P. A. Kuntz, R. D. Christie, and S. S. Venkata, "Optimal vegetation maintenance scheduling of overhead electric power distribution systems," *IEEE Transactions on Power Delivery*, vol. 17, no. 4, pp. 1164–1169, 2002.

[6] A. H. Sanstad, Q. Zhu, B. Leibowicz, P. H. Larsen, and J. H. Eto, "Case studies of the economic impacts of power interruptions and damage to electricity system infrastructure from extreme events," Lawrence Berkeley National Laboratory, Tech. Rep., 2020.

[7] P. Dehghanian, B. Zhang, T. Dokic, and M. Kezunovic, "Predictive risk analytics for weather-resilient operation of electric power systems," *IEEE Transactions on Sustainable Energy*, vol. 10, no. 1, pp. 3–15, 2018.

[8] U. Salman and Z. Wang, "Enhancing grid resilience to extreme events: A synergistic framework integrating vegetation dynamics and microgrid capabilities," *Sustainable Energy, Grids and Networks*, p. 102094, 2025.

[9] U. Salman, Z. Wang, F. Chen, M. Acquah, and D. Stevens, "Risk-aware vulnerability assessment: Mesh-view grid mapping for distribution system resilience," in *2025 IEEE Kiel PowerTech*. IEEE, 2025, pp. 1–6.

979-8-3315-8138-1