### Title

Decision-Dependent Resilience Enhancement Strategy for Distribution Systems Against Endogenous Wildfires




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# Decision-Dependent Resilience Enhancement Strategy for Distribution Systems Against Endogenous Wildfires

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***Abstract*—The increasing frequency and severity of wildfires pose significant threats to utility infrastructure and community safety. Wildfires can be ignited due to component failures under extreme weather conditions. System hardening measures aimed at preventing these failures can reduce the probability of endogenous wildfire ignition, introducing decision-dependent uncertainty (DDU). However, existing methods that consider such DDU typically assume independent component failures, neglecting the critical interdependencies between components destroyed by wildfire and those affected by their spread. These interdependencies render such methods inadequate. To address this, we propose a novel formulation that incorporates both wildfire-ignition DDU and a second type of DDU — the interdependency between wildfire-ignited and wildfire-affected components. We develop a two-stage wildfire-preventive decision-dependent resilience enhancement (WDDRE) model for distribution systems. The model optimizes line hardening, distributed generation allocation, and network reconfiguration to enhance system resilience by preventing endogenous wildfire ignition caused by component failures. Numerical experiments demonstrate the effectiveness and superiority of the WDDRE model, showcasing its robustness in managing wildfire stochasticity and the two kinds of DDUs related to planning decisions, significantly reducing potential wildfire risks.**

***Index Terms*—Decision-dependent uncertainty, resilience enhancement, wildfire, distribution system, stochastic optimization.**

## NOMENCLATURE

*Sets*

| | |
|---|---|
| $\Omega^N, \Omega^{sub}$ | Set of buses and substations. |
| $\Omega^L, \Omega^{FL}$ | Set of lines and lines that may ignite wildfires. |
| $T$ | Set of time periods. |
| $\Omega^w$ | Set of wildfire scenarios. |
| $\Omega^S$ | Set of lines with installed switches. |
| $\mathcal{U}$ | Set of endogenous wildfire damage portfolio. |

*Indices*

| | |
|---|---|
| $i/j, (i, j)/ij$ | Index of bus and line from bus $i$ to bus $j$. |
| $t$ | Index of time period. |
| $w$ | Index of wildfire spread scenario. |

*Parameters*

| | |
|---|---|
| $c_{ij}^h$ | Hardening cost of line $(i, j)$. |
| $c_i^g$ | DG allocation cost at bus $i$. |
| $c_i^d$ | Weighted load shedding cost at bus i. |
| $C^L, C^G$ | Budget for line hardening and DG allocation. |
| $P_{i,t}^{D,w}, Q_{i,t}^{D,w}$ | Active and reactive demand on bus $i$ at time $t$ under scenario $w$. |
| $\overline{P}_{ij}^L, \overline{Q}_{ij}^L$ | Active and reactive power capacity of line $(i, j)$. |
| $R_{ij}, X_{ij}$ | Resistance and reactance of line $(i, j)$. |
| $\overline{P}_i^g, \overline{Q}_i^g$ | Active and reactive DG output limit at bus $i$. |
| $\underline{R}_i, \overline{R}_i$ | Ramping-up / down rate of DG at bus $i$. |
| $\underline{U}_i, \overline{U}_i$ | Squared voltage limit at bus $i$. |
| $x_{ij}^s$ | Binary parameter of switch installation status, equals 1 if line $(i, j)$ is installed with switch, 0 otherwise. |
| $\eta_w$ | Probability of wildfire scenario $w$. |
| $\xi_{ij,t}^{l_0,w}, \xi_{ij,t}^{l_1,w}$ | Binary parameter indicating line status at time $t$ under wildfire $w$ with / without line hardening, equals 1 if line $(i, j)$ is damaged, 0 otherwise. |
| $I_{FL}^w$ | One-hot vector denoting the line index that ignites a wildfire. |

*Variables*

| | |
|---|---|
| $f_{ij}$ | Fictitious flow of line $(i, j)$. |
| $s_{ij}$ | Binary variable of line switch status at line $(i, j)$; equals 1 if the switch is closed, 0 otherwise. |
| $x_{ij}^h$ | Binary variable of line hardening decision at line $(i, j)$; equals 1 if the line is hardened, 0 otherwise. |
| $x_{ij}^g$ | Binary variable of DG allocation decision at bus $i$; equals 1 if a DG is allocated, 0 otherwise. |

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| | |
|---|---|
| $u_{ij,t}^{w}$ | Binary variable of line status, equals 1 if line $(i, j)$, 0 otherwise. |
| $p_{ij,t}^{L,w}, q_{ij,t}^{L,w}$ | Active and reactive power on line $(i, j)$ at time $t$ under wildfire $w$. |
| $p_{ij,t}^{sub,w}, q_{ij,t}^{sub,w}$ | Active and reactive power output of substation at bus $i$ at time $t$ under wildfire $w$. |
| $p_{ij,t}^{g,w}, q_{ij,t}^{g,w}$ | Active and reactive power output of DG at bus $i$ at time $t$ under wildfire $w$. |
| $U_{i,t}^{w}$ | Squared voltage magnitude of bus $i$ at time $t$ under wildfire $w$. |
| $\alpha_{i,t}^{w}$ | Load shedding coefficient of bus $i$. |

# I. Introduction

## A. Motivation

WILDFIRES have become increasingly frequent and severe worldwide due to human activities and climate change. These catastrophic events not only threaten utility infrastructure and the natural environment but also jeopardize the lives and property of nearby communities. For example, the 2009 Black Saturday wildfires in Victoria, Australia, caused 173 deaths [1]. In 2011, wildfires in Bastrop led to two fatalities and over \$300 million in damages [2], and in 2018, the Camp Fire in California — one of the most destructive wildfires in U.S. history — claimed 85 lives and caused approximately \$9.3 billion in damage to residential property [3]. These high-profile incidents underscore the urgent need for effective risk management and mitigation strategies in wildfire-prone regions.

Wildfire ignitions can be categorized as ***exogenous*** and ***endogenous***. Exogenous wildfires originate from external sources, such as lightning or human activity, and affect power systems by damaging infrastructure. In contrast, ***endogenous wildfires*** are triggered by faults within the power system itself, where power lines or equipment come into contact with surrounding vegetation, causing sparks or arcing that ignite fires. Compared to exogenous wildfires, endogenous wildfires are more complex, as they are influenced by the system's structural robustness and operational dynamics, and can lead to cascading effects across the grid due to the wildfire's spread.

The importance of addressing endogenous wildfires is underscored by historical data and incidents. During periods of drought and heatwaves, fires attributed to electrical equipment failures can account for up to 30% of total ignitions [4]. This risk is compounded by aging utility infrastructure worldwide. For instance, the Victorian Bushfires Royal Commission reported that 5 of 15 fires it examined were initiated by failures of electrical assets [5]. Moreover, the 2017 Wine Country fires and the 2018 Camp Fire in California were both traced to electrical faults involving PG&E equipment or associated third-party installations [6]. These examples highlight the need for proactive resilience strategies to mitigate wildfire risks originating within power systems.

In distribution systems, the condition of line conductors, towers, and other load-bearing equipment significantly influences the probability of unanticipated line faults [7]. System hardening measures, including preemptive equipment upgrades and infrastructure fortifications, can be implemented during the planning stage to reduce the likelihood of endogenous wildfire ignition by mitigating the risk of component faults. These endogenous wildfires originate internally due to system equipment failures. Crucially, these hardening decisions directly alter the probability of such failures and thus influence whether, where, and how frequently endogenous wildfires are initiated, introducing what is known as ***decision-dependent uncertainty (DDU)***. Unlike traditional exogenous-driven uncertainties (e.g., lightning-induced wildfires), this uncertainty explicitly depends on resilience planning decisions, making its accurate modeling essential but challenging.

Besides, once a wildfire is ignited, it can spread rapidly, causing damage to nearby components and creating additional faults in the system. The interdependency between ***wildfire-ignited components*** (those that initiate the wildfire due to component failure) and ***wildfire-affected components*** (those subsequently damaged by wildfire spread) is critical for accurately assessing risk. However, these interdependencies, themselves decision-dependent, are often overlooked. For example, a hardened line is less likely to fail, reducing both the likelihood of wildfire ignition and subsequent damage to adjacent system components. Thus, a faulted line that ignites a wildfire can have cascading effects, significantly altering the risk profile of the entire system. Thus, explicitly modeling both types of DDU—wildfire ignition and subsequent wildfire-induced disruption—is essential for effective resilience planning against endogenous wildfires.

## B. Related Work and Research Gaps

Much of the existing research and industry applications primarily emphasize operational strategies designed to manage immediate wildfire threats or mitigate ongoing fire impacts. Utility companies, such as San Diego Gas & Electric (SDG&E), Southern California Edison (SCE), and Pacific Gas and Electric (PG&E), have implemented many initiatives including situational awareness, forecasting, as well as some advanced technologies [8], [9], [10]. Operational programs like PG&E's Public Safety Power Shutoff (PSPS) and Enhanced Powerline Safety Settings (EPSS) are designed to reduce wildfire risk but can also cause significant power disruptions [11]. Besides, there are also studies addressing the interaction between power systems and wildfires from operational aspects. In [12], an optimization framework is proposed to both minimize wildfire risk and maximize the amount of load that can be delivered through optimized power shut-offs. In [13], a stochastic programming model for resilience enhancement of distribution systems under an approaching wildfire is proposed by considering the dynamic line rating of the overhead lines. In [14], a network reconfiguration model is proposed to decrease the wildfire ignition probabilities by alleviating the levels of power flows through vulnerable parts of the system. In [15] proposes a two-stage stochastic programming model for preemptive de-energization planning by considering both endogenous and exogenous wildfires. These operational measures, though effective in reducing wildfire ignition, often result in large-scale customer outages, highlighting a trade-off between safety and service continuity.

Nevertheless, preventing wildfires is far more cost-effective than combating and rebuilding after them [4]. Thus, strategic investments focused on preventing catastrophic wildfires are crucial. From a standards perspective, planning-oriented resilience expectations are becoming increasingly codified. For example, NERC TPL-001-4 [16] requires planners to evaluate the impact of extreme events. The California Public Utilities Commission (CPUC) Wildfire Mitigation Plan [17] addresses system hardening measures to improve wildfire prevention. Complementary guidelines, such as IEEE Std 1656-2010 [18], provide technical criteria for wildlife protective distribution equipment. Besides, there are also studies regarding planning-oriented resilience models against wildfires. In [19], a two-stage robust optimization model is proposed for expansion planning that can maximize the supplied power to the end-users while limiting the risk of wildfire ignition. In [20], a two-stage model and tractable methods are proposed to optimize the upgrade of transmission systems considering multiple resilience enhancement designs. In [21], a tri-level defender-attacker-defender model is constructed to make system hardening decisions for distribution systems under natural disasters, given available resources and operational restoration measures. In [22], a two-stage stochastic programming model is proposed to achieve distribution system planning under both emergency and normal scenarios by utilizing line hardening, distributed generation placement, mobile emergency generator and switch location. However, both the underlying analytical tools in these standards and the existing literature still treat wildfire ignition as exogenous or independent factors, ignoring the critical dimension of the DDU.

While some recent studies have incorporated DDU in resilience planning in certain extreme weather events like hurricanes or ice storms, these methods can only address the first type of DDU, i.e. wildfire ignition uncertainty. In [23], a tri-level resilience enhancement strategy is proposed considering the coupling of the system hardening decisions and the damage uncertainty. In [24], a scenario-wise decision-dependent ambiguity set is constructed to model the relationship between preventive resilient enhancement measures and the related extreme weather-induced contingencies. In [25], a two-stage risk-informed decision-dependent resilience planning model is proposed. The model incorporates the decision-dependent line failure uncertainties introduced by planning decisions and exogenous ice storm-related uncertainties. All these approaches assume independent component failures, neglecting the critical interdependency unique to wildfire scenarios—the linkage between wildfire-ignited components and wildfire-affected components. They fail to consider the second type of DDU, which involves the interdependency between wildfire-ignited and wildfire-affected components in endogenous wildfire scenarios. This interdependency makes existing models inadequate, as they do not capture the complex dynamics of wildfire propagation and its impact on the system. Consequently, no existing approach jointly models the ignition and spread processes as decision-dependent and interrelated—two characteristics intrinsic to endogenous wildfire behavior. This gap undermines the effectiveness of resilience planning and motivates a new framework.

## C. Our Contributions

To address these critical gaps, this research introduces a novel formulation that captures DDUs associated with investment decisions and the complex interdependencies between wildfire-ignition components and wildfire-affected components. To the best of our knowledge, we are the first to propose such a formulation that integrates these interdependencies within a DDU framework, providing a more accurate and robust representation of wildfire risks. Based on this, we develop a two-stage wildfire-preventive decision-dependent resilience enhancement (WDDRE) model for distribution systems, providing a planning-oriented approach for resilience enhancement strategies against wildfires. The WDDRE model optimizes line hardening, distributed generators (DGs) allocation, and network reconfiguration to reduce the probability of wildfire ignition while ensuring continuous load delivery. Structurally, the model constitutes a two-stage stochastic optimization problem that incorporates DDU. The contributions of this paper are as follows:

- We develop a customized cellular automaton model to simulate endogenous wildfires triggered by component failures under extreme weather conditions. Distinct from studies that assume exogenous or fixed ignition points, we couple this automaton with a fragility-based ignition model to generate decision-dependent wildfire scenarios. This enables scalable and realistic scenario generation under endogenous wildfire threats.
- We propose a novel modeling technique to simultaneously quantify two interdependent forms of DDUs: (i) the impact of system hardening decisions on wildfire ignition probabilities, and (ii) the cascading influence of ignition points on subsequent component disruption during wildfire spread. To the best of our knowledge, this is the first method that jointly models ignition- and spread-coupled DDUs, enhancing the robustness of resilience planning under complex endogenous wildfire dynamics.
- We propose a two-stage wildfire-preventive decision-dependent resilience enhancement (WDDRE) model for distribution systems, integrating the proposed DDU modelling. The first stage makes investment decisions on component hardening, DG allocation, and network reconfiguration. The second stage evaluates multi-period operational costs under endogenous wildfire contingencies influenced by first-stage investments. Numerical experiments demonstrate that the proposed method effectively reduces wildfire risks and ensures continuous power supply under wildfire-prone conditions. The results validate the model's robustness in managing uncertainties and enhancing the resilience of distribution systems against wildfires.

The remainder of the paper is organized as follows. In Section II, we describe the proposed cellular automaton method and the modeling of DDUs under endogenous wildfires. Section III describes the mathematical formulation of

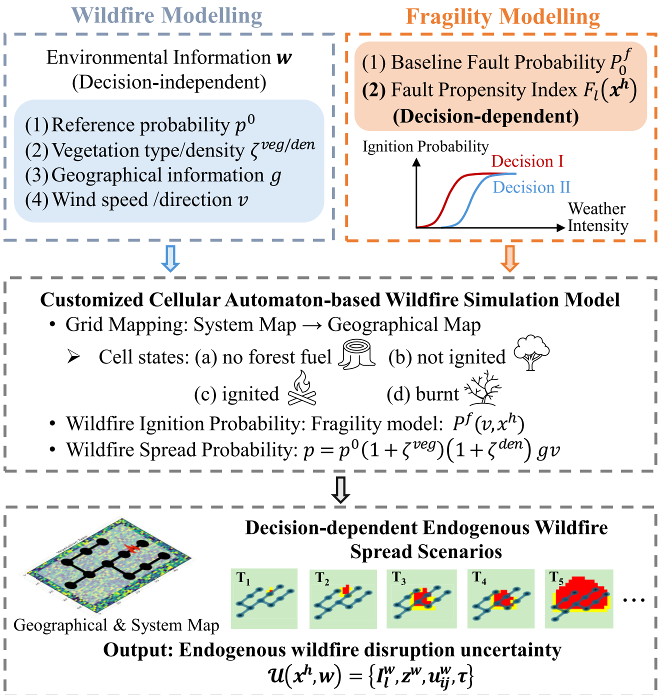



Fig. 1. Endogenous wildfire scenario modeling process via the customized cellular automation model.

the proposed two-stage WDDRE model. Section IV presents case studies and analyzes the results. Section V concludes this study.

## II. Decision-Dependent Uncertainty Sets Considering Line Interdependency Under Endogenous Wildfires

Regarding the long-term resilience enhancement against wildfires, the uncertainty associated with the component failure within the power system is primarily influenced by two major factors: (1) the hardening decision, which is endogenously influenced by planning decisions; (2) the intensity and spatial-temporal spread process of wildfires, which are exogenously influenced by environmental factors. The former uncertainty introduced DDU between planning decisions and the onset of wildfires. In the context of endogenous wildfires, there is also interdependency between wildfire-ignition lines and wildfire-affected lines, which is another resulting DDU of planning decisions. The latter uncertainty was associated with DIU. In this section, we construct a novel scenario-wise decision-dependent uncertainty set to model the endogenous wildfire contingency distribution by considering both types of DDUs and the DIU.

### A. Endogenous Wildfire Scenario Modeling

In this section, we design a customized cellular automation model to simulate the onset and spread of endogenous wildfires, considering both system design and environmental factors. Unlike traditional methods, which are primarily limited to randomly simulating wildfire spread from predetermined ignition points, our approach captures how planning decisions directly influence the probability and location of wildfire ignitions. This integration allows us to generate more targeted wildfire scenarios considering DDU, providing strategically relevant inputs for the WDDRE model. The framework is illustrated in Fig. 1. To model the distribution of potential contingencies, we simulate $|N_w|$ discrete scenarios to represent the spread process of wildfires. Each scenario is a multi-period dispatch operation under wildfire disruption over a one-day time horizon. We assume that at most one component fault will occur and ignite wildfire within the horizon.

Given the geographical footprint of the distribution system, the whole system will be divided into a two-dimensional grid based on the designed resolution. Then, the whole area will be divided into small cells represented by rectangular areas. Then, a mapping between the grid cells and the buses and distribution lines will be constructed based on their geographic locations. Let $z_i \in \mathcal{Z}$ denote the cell that bus $i$ is located and $\mathcal{Z}_{ij} \subset \mathcal{Z}$ denote the cells that distribution line $(i, j)$ spans. In the following section, we will introduce the procedure of the proposed cellular automation model.

First, we simulate electrical component faults and the onset of wildfire. We mainly consider faults on power lines to ignite wildfires since they are more prone to failures than other electrical components due to environmental factors such as lightning and wind [26]. We denote $\Omega^{FL} \subset \Omega^{L}$ as the wildfire-ignition line set, which contains lines that may ignite wildfires. In each time period $t \in T$, a fault may occur at line $l_{ij}^f \in \Omega^{FL}$ with probability $p_l^f$. The fault probability can be influenced by both exogenous environmental factors and endogenous hardening decisions. This introduces the so-called wildfire-ignition DDU and will be discussed in detail in the next section. We assume that the failure probability is independent among candidate lines. It should be noted that this setting can be easily extended to consider more kinds of faults on buses and generators.

Since the failure rate varies among different lines, we adopt a weighted sampling approach to simulate line fault in each scenario. Given the line failure probability portfolio, the failure weight of each line can be calculated as:

$$w_{ij}^f = \frac{p_{ij}^f}{\sum\limits_{ij \in \Omega^{FL}} p_{ij}^f}, \quad ij \in \Omega^{FL} \tag{1}$$

Here, $w_{ij}^f$ represents the likelihood of each line being the initiating point of a wildfire relative to the others. Then, these weights can be converted into a cumulative distribution. For each line $(i, j)$, the cumulative weight $W_k^c$ for the $k$-th line in the candidate list can be expressed as $W_k^c = \sum_{i=1}^{k} w_i^f$. Then, we can perform weighted sampling via Monte Carlo simulation to determine a faulted line $I_l^w$. Since each line passes through multiple cells, we further randomly sample a cell $z_k^w \in \mathcal{Z}_{ij}$ as the ignition cell of wildfire.

To simulate the progress of a wildfire, we employ a cellular automaton method with propagation rules listed in [27]. It should be noted that both the propagation rules and the environmental information required by our model can be collected either from historical datasets or calibrated based on specific environmental conditions relevant to a particular geographical location or operational scenario. Each cell has four states in each time slot as shown in Fig. 1: (a) cell has no vegetation fuel; (b) cell has unignited vegetation fuel; (c) cell has ignited vegetation fuel; (d) cell has fully burnt fuel. For components in $\Omega^{FL}$, there are two states: normal ($\mu_{ij,t}^{l,w} = 0$) or at fault ($\mu_{ij,t}^{l,w} = 1$). For other components, the states can be normal ($u_{ij,t}^{w} = 0$) or damaged ($u_{ij,t}^{w} = 1$) due to the progress of wildfires. For each fault line from the fault period to the end of the time horizon, the cell(s) that contains the faulted line segment will be initialized in state (c). Let the onset time of the wildfire $\tau$ be the time that the line fault occurs; in the following time period, the grid state will be updated on a rolling basis to generate a wildfire scenario. Under a candidate wildfire scenario $w$, the state of cell $z_i$ at time $t$, denoted by $s_{z,t}$, is influenced by environmental factors based on a set of defined rules:

(i) If $s_{z,t-1} = b$ (the unburned fuel state), it has a probability $p_{z,t}$ to be ignited and its state will transfer to $s_{z,t} = c$ (the ignited fuel state);

(ii) If $s_{z,t-1} = c$, then the state will transfer to $s_{z,t} = d$ (the fully burning state);

(iii) If $s_{z,t-1} = d$, the state will stay unchanged $s_{z,t} = d$. The flames can spread to its 8 adjacent cells indexed by $\tilde{z}$. Those adjacent cells can be ignited with probabilities $p_{\tilde{z},t}$ if their previous states $s_{\tilde{z},t-1} = b$. The probability of being ignited $p_{\tilde{z},t}$ is influenced by environmental factors and can be calculated as:

$$p_{\tilde{z}t} = p_{\tilde{z}}^{0}(1 + \zeta_{\tilde{z}}^{veg})(1 + \zeta_{\tilde{z}}^{den})g_{\tilde{z}}v_{\tilde{z}t}^{w} \tag{2}$$

where $p_{\tilde{z}}^{0}$ is the base probability that cell $\tilde{z}$ will be burnt under flat terrain with no wind; $\zeta_{\tilde{z}}^{veg}$ and $\zeta_{\tilde{z}}^{den}$ represent vegetation type and density, respectively; $g_{\tilde{z}}$ represents the geographical information and $v_{\tilde{z}t}^{w}$ represents wind information such as speed and direction. These environmental parameters are treated as decision-independent uncertainties (DIUs). Planners and operators can calibrate or sample them from site-specific data for particular service territories or scenarios without modifying the proposed optimization framework.

If a wildfire spreads to a cell containing other distribution lines, it will cause line damage. We record the line damage status $u_{ij,t}^{w}$ for each time period. After the end of time horizon $T$, we can obtain the endogenous wildfire damage portfolio $\mathcal{U}(\boldsymbol{x^h}, \boldsymbol{w})$. Here, the environmental factors $\boldsymbol{w}$ (DIU) are inherently incorporated. In addition, wildfire disruption uncertainty will also be influenced by planning decision $\boldsymbol{x^h}$ (DDU) and will be explained in the next section.

## B. Decision-Dependent Wildfire Contingencies Considering Line Interdependency

In the context of endogenous wildfires, there are two kinds of DDUs related to system-hardening decisions and the random nature of wildfires: (1) Decision-dependent wildfire ignition uncertainty (DDU 1); (2) Decision-dependent wildfire disruption uncertainty (DDU 2)

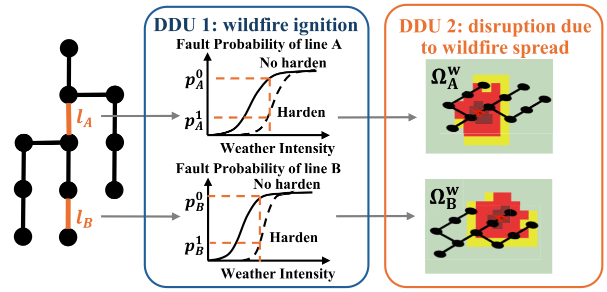



Fig. 2. Illustration of two kinds of DDUs in planning decisions in endogenous wildfires.

DDU 1 refers to uncertainty regarding the initiation of wildfires, determined by factors such as line faults, weather conditions, and system-hardening measures. DDU 2 influences the damage status of components during the wildfire spread, affected by the spatial and temporal factors of DDU 1 and environments. An illustrative figure is shown in Fig. 2. Wildfire-ignition lines $\Omega^{L} = \{l_A, l_B\}$ are lines that can potentially ignite a wildfire. Wildfire-affected lines $\Omega^{L}/\Omega^{FL}$ are lines potentially damaged due to the spread of the wildfire, which is influenced by the ignition location. System-hardening decisions (e.g., which lines to harden) directly impact the fragility curves of wildfire-ignition lines. Under different weather intensities, this directly influences the occurrence of wildfire ignition on certain lines, introducing DDU 1. After ignition, the location of the wildfire influences the spread area and the lines that are damaged by the wildfire. For instance, as shown in Fig. 2, the areas affected by a wildfire ignited by line A and line B are different. This interdependency between wildfire-ignited lines and wildfire-affected lines links the system-hardening decisions with the damage status of wildfire-affected lines, introducing DDU 2. Essentially, DDU 2 captures how the spread of wildfire (after ignition) influences the system and the resulting damage to infrastructure.

To model these interdependencies, we propose a new modeling technique to characterize both types of DDUs simultaneously, capturing the interactions between system hardening, wildfire ignition, and the subsequent disruption.

*1) Decision-Dependent Wildfire Ignition Uncertainty:* To characterize the endogenous wildfire ignitions within $\Omega^{FL}$, we adopt the fragility model proposed in [28] to link the failure probability of distribution lines with the weather intensity, $v^g$ and system hardening designs $x^h$:

$$P^{f}(v^g, x^h) = \begin{cases} P_0^{f} & v^g < \underline{V}(x^h) \\ (1-P_0^{f})P^{wi} + P_0^{f} & \underline{V}(x^h) \leq v^g \leq \overline{V}(x^h) \\ 1 & v^g \geq \overline{V}(x^h) \end{cases} \tag{3}$$

where $P_0^{f}$ represents base fault probability, $P^{wi}$ is the wind-related fault probability influenced by the 3-second wind gust speed $v^g$. $\underline{V}$ and $\overline{V}$ are parameters representing the lower and upper wind thresholds, which are functions of system hardening decisions $x^h$ and can be expressed as:

$$\underline{V}_l(x^h) = V_l^{cr} + \epsilon F_l(x_l^h) \tag{4}$$
$$\overline{V}_l(x^h) = V_l^{co} + \epsilon F_l(x_l^h) \tag{5}$$

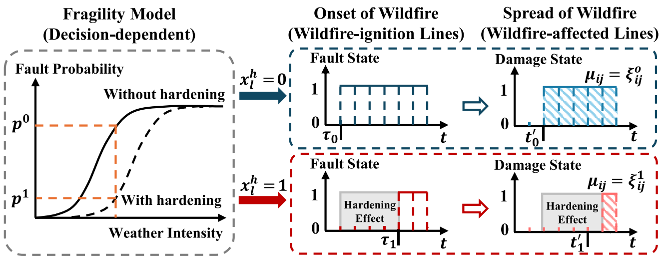



Fig. 3. Illustration of decision-dependent wildfire-ignition and damage status with/without hardening design decision.

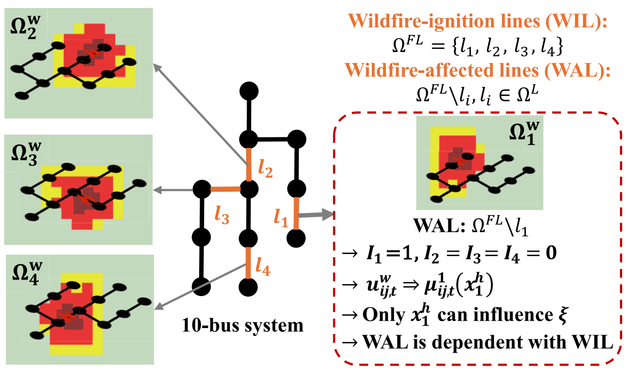



Fig. 4. An illustrative example of modeling the interdependency between wildfire-ignition lines and wildfire-affected lines.

Here, $F_l$ is the Fault Propensity Index [28] that influences the line fragility curve, taking into account its structural mechanical strength and precarious vegetation management.

Preventive system hardening measures will have a positive effect and decrease the fault probability under certain intense weather conditions, thus directly delaying or even preventing potential wildfires. An illustrative example is shown in Fig. 4.

*2) Decision-Dependent Wildfire Disruption Uncertainty Considering Line Interdependency:* As stated in II-A, line damage occurs when a grid cell containing the corresponding line segment is burnt during the spread of wildfire. Since the wildfire ignition is decision-dependent, the resulting wildfire spread progress and the line damage status will also be decision-dependent. Therefore, there exists line interdependency between wildfire-ignition lines and wildfire-affected lines. Consider a wildfire $w$ ignited by line $l \in \Omega^{FL}$, let $u^w_{ij,t}(x^h_l)$ denote the resulting line damage status. The fault probability will decrease if the line is structurally hardened. Then here comes two challenges:

(I) We can not generate the sample of $u^w_{ij,t}(x^h_l)$ before knowing $x^h_l$, which requires solving the planning optimization problem. However, generating all possible wildfire scenarios is impossible since the number of $x^h_l$ boosts exponentially with the size of the system.

(II) Given certain $x^h_l$, we can obtain the corresponding $u^w_{ij,t}(x^h_l)$ under wildfire ignited by line $l$ (line interdependency). On the one hand, $u^w_{ij,t}(x^h_l)$ is actually influenced by all lines within $\Omega^{FL}$ and should be considered during modeling; on the other hand, only one $x^h_l$ will be effective for a specific wildfire scenario ignited by $l$.

To tackle these challenges, we propose a novel modeling strategy to incorporate both the decision-dependent line damage status and the dependency between wildfire-ignited lines and wildfire-affected lines.

For challenge (a), consider a specific wildfire scenario ignited by line $l$, we decompose the line damage status $\mu^{l,w}_{ij,t}(x^h_l)$ into two conditional independent binary variables $\xi^{0,w}_{ij,t}$ and $\xi^{1,w}_{ij,t}$, which represent the line damage status during wildfire propagation with or without hardening wildfire-ignition line $l$ respectively:

$$\mu^{l,w}_{ij,t} = (1 - x^h_l)\xi^{l_0,w}_{ij,t} + x^h_l \xi^{l_1,w}_{ij,t} \tag{6}$$

Thus, $\mu^{l,w}_{ij,t}$ can be represented as an explicit function of $x^h_l$. Then, $\xi^{l_0,w}_{ij,t}$ and $\xi^{l_1,w}_{ij,t}$ can be determined in advance during the scenario generation process to incorporate the line damage DDU influenced by line $l$, which can be illustrated in Fig. 4. However, (6) can only accommodate only one line hardening decisions and is inadequate to deal with challenge (b).

To address the challenge (b), since only the corresponding decision variables $x^h_l$ can be effective under a wildfire ignited by line $l$, we introduce an additional one-hot vector $I^w_{FL}$ denoting the line that ignites a wildfire. Each element $I^w_l \in I^w_{FL}$ is a binary parameter indicating if line $l$ ignite the wildfire in scenario $w$. Then, we further improve the modeling in (6) to incorporate line interdependency as:

$$u^w_{ij,t} = \sum_{l \in \Omega^{FL}} I^w_l \mu^{l,w}_{ij,t} = \sum_{l \in \Omega^{FL}} I^w_l [(1 - x^h_l)\xi^{l_0,w}_{ij,t} + x^h_l \xi^{l_1,w}_{ij,t}] \tag{7}$$

Fig. 4 shows an illustrative example of how (7) can incorporate the line interdependency between wildfire-ignition lines and wildfire-affected lines. Consider a 10-bus system, the candidate line set that may lead to endogenous wildfire containing 4 lines: $\Omega^{FL} = \{l_1, l_2, l_3, l_4\}$. Then, the wildfire scenario set can be classified into 4 subsets: $\Omega^w = \{\Omega^w_1, \Omega^w_2, \Omega^w_3, \Omega^w_4\}$. For a certain scenario $w$, if the wildfire is ignited by $l_1$, the corresponding index $I^w_1 \in \Omega^{FL}$ will be set as 1 and other indexes $I^w_2, I^w_3, I^w_4$ will be set as 0. Then, there is $I^w_{FL} = [1, 0, 0, 0]$ and (7) can be calculated as:

$$u^w_{ij,t} = \sum_{l \in \Omega^{FL}} I^w_l \mu^{l,w}_{ij,t} = I^w_1 \mu^{1,w}_{ij,t} = \mu^{1,w}_{ij,t} \tag{8}$$

Then, (7) will degenerate to (6) and only $\xi$ related with line $l_1$ and the corresponding hardening decision $x^h_1$ will be effective. Given the above illustrative example, it can be noticed that by using (7), only $\xi^{l_0,w}_{ij,t}$ and $\xi^{l_1,w}_{ij,t}$ related with $x^h_l$ will be effective given certain wildfire scenario $w$. Thus, the inherent line interdependency can be properly incorporated during endogenous wildfire modeling. Another key advantage is that by using this modeling technique, we only need to sample $I^w_l$, $\xi^{l_0,w}_{ij,t}$ and $\xi^{l_1,w}_{ij,t}$ for all line $l \in \Omega^{FL}$ and $(i, j) \in \Omega^L$ independently in the phase of scenario generation, and thus avoid computationally intractability.

Finally, by incorporating (3)-(8) into the scenario modeling process as stated in section II-A, we can obtain a scenario-wise uncertainty sets considering investment-related DDU, line interdependency DDU and wildfire-related DIU. The endogenous wildfire damage portfolio can be expressed as: $\mathcal{U}(\boldsymbol{x^h}, \boldsymbol{w}) = \{\boldsymbol{I^w_l}, \boldsymbol{z^w}, \boldsymbol{u^w_{ij}}, \boldsymbol{\tau}\}$, as is shown in Fig. 1. Unlike

**Algorithm 1** Scenario Generation Process

**Input:** Geographical Map, Environmental Information,
**Input:** System Information, Fragility Model
**for** scenario $w \in \Omega^w$ **do**
 ▷ ***DDU 1 - Line Hardening***
 Calculate $P^f_0 = P^f(v, x^h = 0)$ and $P^f_1 = P^f(v, x^h = 1)$ using the fragility model (3).
 Sample initiation status $\xi^{l_0,w}_{ij,t}$, $\xi^{l_1,w}_{ij,t}$ and the related onset time $\tau_0$, $\tau_1$; record ignition cell $z^w_k$
 ▷ ***Cellular Automation Method***
 Set $s_{z,\tau_{0/1}} = c$
 **for** $t = min\{1, \tau_0/\tau_1\}, \ldots, |T|$ **do**
  Wildfire spread simulation (Section II-A)
  Obtain each cell state $s_{z,t}$
  ▷ ***DDU 2 - Line interdependency***
  Obtain component damage status $u^w_{ij,t}(s_{z,t})$
 **end for**
**end for**
**return** The endogenous wildfire damage portfolio: $\mathcal{U}(\boldsymbol{x^h}, \boldsymbol{w}) = \{\boldsymbol{I^w_l}, z^w, \boldsymbol{u^w_{ij}}, \tau\}$

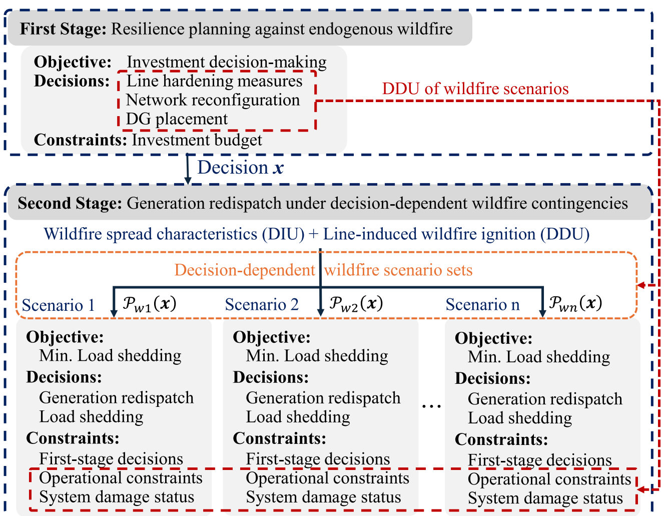



Fig. 5. The wildfire-preventive decision-dependent resilience enhancement (WDDRE) model.

conventional approaches that fix ignition points or assume decision-independent failures, our scenario construction is explicitly contingent on first-stage decisions. This enables us to quantify how planning choices shift ignition risk and damage paths, to isolate the effect of DDUs, and to measure the performance loss when such dependencies are ignored—providing concrete guidance for robust investment planning. The procedure for scenario generation is shown in Algorithm 1.

## III. The Wildfire-Preventive Decision-Dependent Resilience Enhancement Model

In this section, we propose a two-stage wildfire-preventive decision-dependent resilience enhancement (WDDRE) model for distribution systems considering the two kinds of DDUs stated in Section II. The WDDRE model is formulated in a two-stage framework, as shown in Fig. 5. The mathematical formulation of the proposed model is explained below.

### A. Objective Function

The objective of the proposed WDDRE model aims to minimize investment costs and maintain the continuous power supply in the face of endogenous wildfires:

$$\min \sum_{(i,j)\in\Omega^{FL}} c^h_{ij} x^h_{ij} + \sum_{i\in\Omega^N} c^g_i x^g_i + \eta_w \mathbb{E}_w[\phi_w(\boldsymbol{x}, \boldsymbol{w})] \tag{9}$$

where

$$\phi_w(\boldsymbol{x}, \boldsymbol{w}) = \min \sum_{t\in T} \sum_{i\in\Omega^N} c^d_i \alpha^w_{i,t} P^{D,w}_{i,t} \tag{10}$$

The first and second terms of (9) are the investment cost of line hardening and DG installation, respectively. The third term is the expected weighted load-shedding during disruptive wildfire propagation. Vectors $\boldsymbol{w}$ contain the second-stage system damage status and decision variables under potential wildfire scenarios.

### B. First Stage: Preventive Line Hardening, DG Allocation and Network Reconfiguration

During the planning stage, the model determines line hardening decisions, DG allocations, and proactive network reconfiguration:

$$\sum_{(i,j))\in\Omega^{FL}} c^h_{ij} x^h_{ij} \le C^L \tag{11}$$

$$\sum_{i\in\Omega^N} c^g_i x^g_i \le C^G \tag{12}$$

$$1 - x^s_{ij} \le s_{ij}, \ \forall (i,j)) \in \Omega^S \tag{13}$$

$$\sum_{j|(i,j)\in\Omega^L} f_{ji} - \sum_{j|(i,j)\in\Omega^L} f_{ij} = d_i, \ \forall i \in \Omega^N \setminus \Omega^{Nsub} \tag{14}$$

$$\sum_{j|(i,j)\in\Omega^L} f_{ij} - \sum_{j|(i,j)\in\Omega^L} f_{ji} \le g_i, \ g_i \ge 1, \ \forall i \in \Omega^{sub} \tag{15}$$

$$-M_1 s_{ij} \le f_{ij} \le M_1 s_{ij}, \ \forall (i,j) \in \Omega^L \tag{16}$$

$$\sum_{(i,j))\in\Omega^L} s_{ij} = |\Omega^N| - |\Omega^{sub}| \quad \forall (i,j)) \in \Omega^L \tag{17}$$

where (11) and (12) are budget constraints on line hardening and DG allocation. Constraint (13)-(17) ensure the radiality of the distribution system [29]. Among them, Constraint (13) ensures that only lines with installed switches can be switched off. Constraint (14) enforces the connectivity via the fictitious flow balance at each non-substation node. $d_i$ represents the fictitious load at bus $i$. Constraint (15) ensures that there will no islanding of a single substation bus. Constraint (16) guarantees only switched-on lines can deliver the virtual commodity. Constraint (17) finally ensures the radiality.

### C. Second Stage: Responsive Generation Re-Dispatch and Load Shedding During Wildfire Contingencies

Given the first stage decisions, the model will minimize the expected operational costs under potential wildfire scenarios by re-dispatching available resources as well as satisfy the operational constraints:

$$u_{ij,t}^{w} = \sum_{l\in\Omega^{l}} I_l^w[(1 - x_l^h)\xi_{ij,t}^{l_0,w} + x_l^h \xi_{ij,t}^{l_1,w}] \tag{18}$$

$$\sum_{j|(i,j)\in\Omega^L} p_{ij,t}^{L,w} - \sum_{j|(j,i)\in\Omega^L} p_{ji,t}^{L,w} = P_{i,t}^{g,w} + P_{i,t}^{sub,w} - (1-\alpha_{i,t}^{w})P_{i,t}^{D,w} \tag{19}$$

$$\sum_{j|(i,j)\in\Omega^L} q_{ij,t}^{L,w} - \sum_{j|(j,i)\in\Omega^L} q_{ji,t}^{L,w} = Q_{i,t}^{g,w} + Q_{i,t}^{sub,w} - (1-\alpha_{i,t}^{w})Q_{i,t}^{D,w} \tag{20}$$

$$U_{i,t}^{w} - U_{j,t}^{w} \le 2(R_{ij}p_{ij,t}^{L,w} + X_{ij}q_{ij,t}^{L,w}) + M_2(2 - u_{ij,t}^{w} - s_{ij}) \tag{21}$$

$$U_{i,t}^{w} - U_{j,t}^{w} \ge 2(R_{ij}p_{ij,t}^{L,w} + X_{ij}q_{ij,t}^{L,w}) + M_2(u_{ij,t}^{w} + s_{ij} - 2) \tag{22}$$

$$-s_{ij}\overline{P}_{ij}^{L} \le p_{ij,t}^{L,w} \le s_{ij}\overline{P}_{ij}^{L} \tag{23}$$

$$-s_{ij}\overline{Q}_{ij}^{L} \le q_{ij,t}^{L,w} \le s_{ij}\overline{Q}_{ij}^{L} \tag{24}$$

$$-u_{ij}^{w}\overline{P}_{ij}^{L} \le p_{ij,t}^{L,w} \le u_{ij}^{w}\overline{P}_{ij}^{L} \tag{25}$$

$$-u_{ij}^{w}\overline{Q}_{ij}^{L} \le q_{ij,t}^{L,w} \le u_{ij}^{w}\overline{Q}_{ij}^{L} \tag{26}$$

$$\underline{U}_i \le U_{i,t}^{w} \le \overline{U}_i \tag{27}$$

$$0 \le P_{i,t}^{g,w} \le x_i^g \overline{P}_i^g \tag{28}$$

$$0 \le Q_{i,t}^{g,w} \le x_i^g \overline{Q}_i^g \tag{29}$$

$$\underline{R}_i \le P_{i,t}^{g,w} - P_{i,t-1}^{g,w} \le \overline{R}_i \tag{30}$$

$$0 \le \alpha_{i,t}^{w} \le 1 \qquad \forall (i,j)\in\Omega^L,\ i\in\Omega^N,\ t\in T,\ w\in\Omega^w \tag{31}$$

Here, constraint (18) models the DDU between line hardening decisions and line damage status under wildfires as is stated in Section II. Constraints (19) and (20) enforce power balance. Constraints (21) and (22) represent the voltage changes along a line given the line status by applying the big-M method. Constraints (23) and (24) impose thermal limits to closed lines. Constraints (25) and (24) impose power flow limits to intact lines. Constraint (27) sets the voltage limit. Constraint (28)-(29) sets the active and reactive output limits of DGs and constraint (30) represents the ramping limits. Note that here only the controllable distributed generators (DGs) are considered, but other forms of DERs can be conveniently added to the model. Constraint (31) limits that load shedding is less than demand.

***Remarks:*** One of the significant advantages of the proposed DDU modeling, as discussed in Section II-B and formulated in (18), is that the resulting optimization problem (9) - (31) is a general two-stage stochastic mixed-integer linear programming problem. This formulation allows the problem to be efficiently solved using commercial solvers such as Gurobi or CPLEX. While there may be computational challenges as the system scale and number of scenarios increase, addressing these large-scale stochastic optimization problems is beyond the primary scope of this research. However, it is worth noting that numerous stage-based and scenario-based decomposition methods have been developed to handle such problems [30]. These methods can be seamlessly integrated with the proposed model to manage computational complexity, thereby ensuring practical applicability in large-scale systems.

## IV. Case Studies

### A. Experiment Settings

In this section, numerical experiments are performed to evaluate the performance of the proposed WDDRE model using the modified IEEE 33-bus and 123-bus test feeders [31]. The first system contains 33 nodes with 1 substation at node 1 and 4 DG units for allocation. The second system contains 123 nodes with 1 substation at node 150 and 6 DG units for allocation. In each system, several nodes are randomly selected as critical load nodes, with a load weight set at 20 to denote higher priority for ensuring continuous power supply. The weights of non-critical load nodes are randomly generated within the interval [1, 10]. The voltage lower and upper limits are set as 0.95 p.u. and 1.05 p.u. respectively. The active and reactive power loads at each bus are randomly generated from intervals [40, 400] kW and [20, 200] kVar.

For endogenous wildfire simulation, each test feeder is mapped into a geographical map as stated in Section II-A. The geographical information, including vegetation type, density, and elevation, is randomly generated. Parameters related to wildfire propagation simulation are referenced from the model stated in [15]. The empirical fragility curve stated in [28] is tuned to reflect different fault probabilities of distribution lines before and after hardening investment. Scenarios are generated via the scenario generation process described in Algorithm 1. Each wildfire scenario containing damage status is generated on a 24-hour horizon with a 1-hour resolution.

For investment parameters, pole replacement with stronger materials is selected as a typical hardening strategy to withstand high environmental stresses. The cost for upgrading each pole is set as \$6000 [24], and the span of two consecutive poles is 100 meters. The active and reactive capacities of DGs are all set to be 250kW and 150kVar, respectively. The capital costs of DG units are set to be 1000\$/kW. All initial investment expenditures are pro-rated to the uniform annual costs based on 10 years lifetime and 2% interested rate [32]. For operational parameters, the load-shedding cost during wildfire contingencies is assumed to be 20\$/kWh [33]. The load-shedding penalty factor $c_i^d$ in (10) is the product of the basic load-shedding cost and the corresponding load weight.

In the following sections, we first present the resilience enhancement results of the proposed WDDRE model. Then, several comparison studies and performance evaluation studies are conducted to demonstrate the efficacy of the proposed method. All models are implemented using Python and are solved using Gurobi 11.02 on a Macbook with M1 CPU and 8GB memory. The convergence tolerance is set as 1%.

### B. Resilience Planning Results of the WDDRE Model

In the modified IEEE 33-bus system, the wildfire ignition line set is $\Omega^{FL} = \{(5,6),(13,14),(16,17),(26,27),(30,31)\}$. The resilience planning result obtained from the proposed WDDRE model is shown in Fig. 6. The total investment

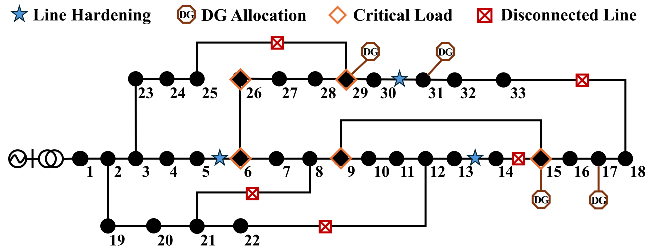



Fig. 6. The optimal resilience enhancement strategy in the modified IEEE 33-bus test system.

TABLE I
PLANNING STRATEGIES WITH DIFFERENT CONSIDERATIONS

| Strategy | Wildfire Stochasticity | DD-WIU | DD-WDU |
|---|---|---|---|
| I | ✓ | ✓ | ✓ |
| II | × | ✓ | ✓ |
| III | ✓ | × | ✓ |
| IV | ✓ | × | × |

cost in the first stage is $1.918 \times 10^6$\$. The expected weight load shedding in the second stage is $107.71 \times 10^3$kW. DGs are strategically allocated at nodes 15 and 29 to provide continuous power supply to critical loads on a local level. Additionally, DGs are allocated not only at critical load nodes but also at other strategic locations, such as nodes 17 and 31, to enhance the grid's resilience by supplying power to the grid and maintaining overall network stability. The distribution lines 5-6, 13-14, and 30-31 are hardened to decrease the probability of endogenous wildfire ignitions. These lines are critical as they are near nodes with high-priority loads. Hardening these lines enhances their mechanical strength, making them less susceptible to faults caused by environmental factors and ensuring continuous power supply to critical loads. Considering the potential spread paths of wildfire, lines 14-15, 8-21, 12-22, 22-26, and 32-33 are disconnected to reconfigure the network. This proactive reconfiguration can achieve a more robust network topology that can withstand the spread of wildfires, thus protecting the overall integrity of the grid.

### *C. In-Sample and Out-of-Sample Performance of the Proposed WDDRE Model*

To verify the efficiency of the proposed two-stage WDDRE model, we compare four planning strategies with different preliminary knowledge of endogenous wildfires, as shown in Table I. Strategy I is the proposed WDDRE model. Strategy II neglects stochasticity during the wildfire occurrence and spread process, and just typical scenarios are utilized to generate the wildfire scenario set. Strategy III ignores the decision-dependent wildfire ignition uncertainty (DD-WIU), assuming constant fault locations and times when generating wildfire scenarios initiated by a specific line. Strategy IV ignores the line interdependency (decision-dependent wildfire disruption uncertainty, DD-WDU), treating line status $u^{w}_{ij,t}$ in equation (18) as input parameters decoupled from first-stage decisions. Since DD-WDU is coupled with DD-WIU, both types of DDUs are ignored in this case.

TABLE II
EVALUATION OF THE EXPECTIVE WEIGHTED LOAD SHEDDING UNDER FOUR COMPARISON STRATEGIES ($1 \times 10^3$ KW)

| Strategy | In-Sample | Out-of-Sample |
|---|---|---|
| I | **107.71** | **260.50** |
| II | 59.54 | 413.12 |
| III | 149.23 | 388.69 |
| IV | 281.24 | 643.39 |

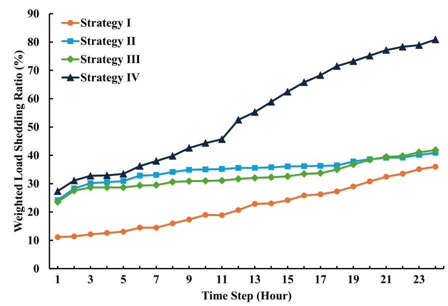



Fig. 7. The curve of average weighted load shedding ratio under out-of-sample wildfire scenarios.

TABLE II shows the in-sample and out-of-sample performances of the four comparison strategies. It can be noticed that although the Strategy I obtained using the proposed method does not achieve the lowest in-sample expectation, it has the lowest expected weighted load shedding in out-of-sample evaluation. Since Strategy II neglects stochasticity and considers only typical scenarios, it exhibits optimism in estimating potential wildfire scenarios, leading to lower in-sample results. However, when evaluating more scenarios with stochasticity, this resulted in a 58.59% increase in load shedding. Strategy III exhibits similar optimism issues since it ignores wildfire ignition uncertainty. However, this issue is mitigated by considering wildfire stochasticity, resulting in better out-of-sample performance than Strategy II. Nevertheless, it still shows a 49.21% increase in load shedding compared to Strategy I. Strategy IV performs the worst in both in-sample and out-of-sample tests since it completely ignores the impact of DDUs brought by system hardening designs, demonstrating the critical role of robust system design. These findings underscore the necessity of jointly modeling both ignition-related (DD-WIU) and spread-related (DD-WDU) uncertainties. Without accounting for these decision-dependent factors, the planner significantly underestimates the disruption risk, leading to suboptimal and overly fragile system designs.

Fig. 7 shows the out-of-sample average load-shedding ratio curve. The results of the Strategy I proposed by our model show the best performance among all time steps, which demonstrates the superiority of the proposed methods. Similar to the results in TABLE II, the results of Strategy II and III are close to each other, suggesting a complementary impact of considering the random nature of wildfire spread and the uncertainty in wildfire ignition.

Moreover, in order to evaluate the performance of the four strategies on power supply reliability and infrastructure resilience, we define two assessment indexes: the Number of Faulted Lines (NFL) and the Aggregate Line Interruption Duration (ALID). The NFL represents the total number of lines damaged during wildfire events, indicating the extent of system damage under wildfires. The ALID represents the total duration of line interruptions due to wildfire spread under a wildfire scenario and can be used to evaluate the interruption duration experienced by customers. The NFL and ALID are calculated as below:

$$\text{NFL} = \sum_{(i,j)\in\Omega^L} (1 - u_{ij}^w), \quad \forall\, w \in \Omega^w \tag{32}$$

$$\text{ALID} = \sum_{t\in T} \sum_{(i,j)\in\Omega^L} (1 - u_{ij,t}^w), \quad \forall\, w \in \Omega^w \tag{33}$$

Fig. 8 depicts boxplots of the NFL and ALID for the four comparison strategies. Fig. 8(a) shows the results for NFL. The medians of NFL for the four strategies are 3, 6, 6, and 17, respectively. This demonstrates that the proposed WDDRE model effectively enhances system resilience by minimizing line damage during wildfires, thereby reducing post-event recovery costs. Additionally, Strategy I has the narrowest span, which demonstrates the robustness of the proposed method. Furthermore, the results of ALID in Fig. 8(b) show similar trends. The proposed WDDRE model demonstrates a comparably narrow span and positive skewness, indicating fewer line interruptions and more stable resilience enhancement performance across various scenarios. Strategies II and III both show higher median ALID and a much larger span than Strategy I, with their medians (38.5 hours) both being 75% higher than that of Strategy I (22 hours). This indicates that neglecting wildfire stochasticity and DD-WIU makes the system more vulnerable and less capable of guaranteeing stable results. Strategy IV shows the worst results in both NFL and ALID metrics, demonstrating that ignoring both DD-WIU and DD-WDU dramatically increases disruption risk and weakens system robustness. This provides further empirical validation of the necessity to explicitly model both DDUs in resilience planning.

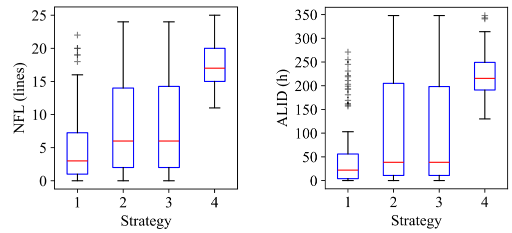
Overall, the comparison studies highlight the effectiveness of the proposed WDDRE model in addressing both stochastic and decision-dependent uncertainties, ensuring a more resilient and robust power distribution system against endogenous wildfire disruptions.

### *D. Contributions of Robust System Designs*

To investigate the contributions of resilience enhancement measures, i.e. line hardening, DG allocation and network reconfiguration, several cases are compared: (1) Case 1: The proposed WDDRE model. (2) Case 2: Proactive network reconfiguration is not considered. (3) Case 3: Line hardening decisions are randomly selected. (4) Case 4: DG allocation is randomly selected. Unless specified otherwise, all parameter settings are kept the same across these cases.

The average weighted load shedding ratio under multiple endogenous wildfire scenarios is shown in Fig. 9. It can be noticed that as the progressing of wildfire, the amount of load shedding increases since more components within the distribution network are affected. However, the load-shedding curve obtained using the resilience enhancement strategy of the proposed WDDRE model (Case 1) remains the lowest among the four cases. Compared with Case 1, the load shedding ratio at the end of the wildfire simulation horizon increases by 3.63%, 7.63%, and 6.55%, respectively. Proactive network reconfiguration can utilize the topology flexibility to decrease load shedding during contingencies. Strategic DG allocation has the capability to supply node loads locally even when the node is disconnected from the main grid. This capability is crucial for maintaining supply to critical loads. Line hardening strategy also has a substantial impact on resilience enhancement. This is because it can lower the probability of igniting endogenous wildfire due to component fault under intense weather conditions. By reinforcing the mechanical strength of critical lines, the likelihood of faults and subsequent wildfires is decreased, thereby postponing or even avoiding wildfire occurrences. By considering multiple resilience enhancement measures, the proposed WDDRE model can effectively achieve a more robust system design, resulting in the lowest load-shedding ratios and demonstrating superior performance in enhancing the resilience of power distribution systems against wildfires.

Furthermore, the median NFL and ALID are the same among Cases 1, 2, and 4 since the line hardening decisions are consistent across these cases (NFL is 3 lines and ALID is 22 hours). This is because these cases do not influence the line-hardening decision-making and therefore have minimal impact on component damage. The main difference lies in the load shedding, indicating that network reconfiguration and DG allocation primarily influence operational resilience. In contrast, Case 3, where line hardening decisions are directly



(a) NFL (b) ALID

Fig. 8. Boxplot of NFL and ALID among different strategies.

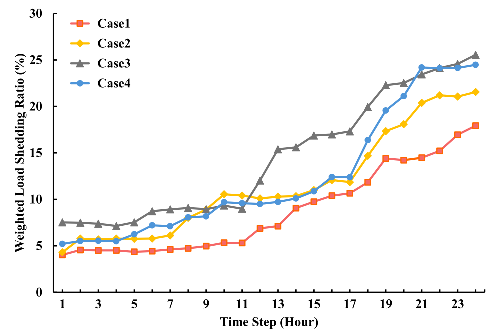



Fig. 9. The curve of average weighted load shedding ratio under different resilience enhancement measures.

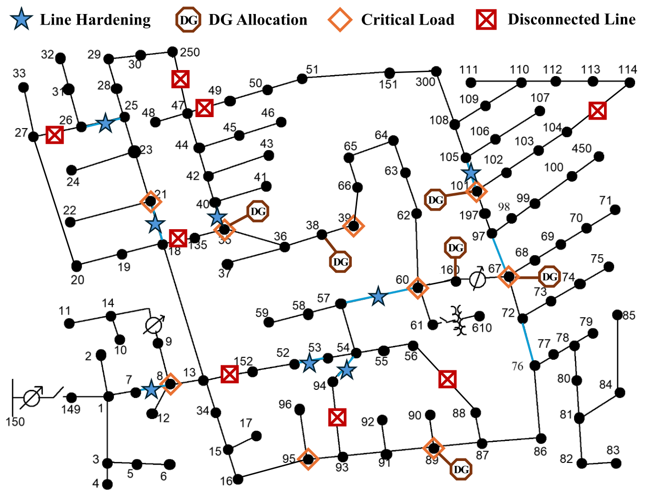



Fig. 10. The optimal resilience enhancement strategy in the modified IEEE 123-bus test system.

influenced, shows substantially higher median and variance for both NFL and ALID compared to the other three cases. The median of NFL is 14 lines and ALID is 189 hours. This emphasizes the significance of system hardening designs. Random line hardening leads to increased vulnerability and higher damage, underscoring the need for strategic planning to enhance the resilience of power distribution systems.

### *E. Scalability of the WDDRE Model*

To demonstrate the scalability of the proposed WDDRE model, the results obtained from the modified IEEE 123-bus test feeder are shown in Fig. 10. Line sets containing lines that may ignite endogenous wildfires are depicted in blue. To balance computational time and solution quality, we stop the optimization process when the optimality gap reaches about 1.5 %. The total investment cost in the first stage is $6.54 \times 10^6$ \$. The expected weight load shedding in the second stage is $2.38 \times 10^7$ kW. DGs are allocated at nodes 35, 38, 67, 89, 101 and 160 to provide continuous power supply to the distribution grid. Similar to the IEEE 33-bus system, not all DGs are allocated on nodes with critical loads. Instead, the placement is strategically designed to enhance the overall resilience of the distribution grid. This ensures that even if some parts of the network are affected by wildfires, other parts can continue to receive power, maintaining a higher load survivability. Critical lines are hardened to decrease the probability of endogenous wildfire ignitions. This is particularly important in a larger system where the impact of a single line failure can propagate more extensively. Despite the increase in system size and complexity, the WDDRE model remains computationally feasible, achieving a 1.5% optimality gap within approximately 20.7 hours. Compared to the smaller feeder, the 123-bus system exhibits a broader spatial distribution of hardening and DG investments, as well as a larger margin of resilience improvement in absolute terms. This suggests that the benefits of jointly modeling DD-WIU and DD-WDU become more pronounced as system scale and network interdependency increase. This demonstrates the model's scalability and practicality for use in large-scale distribution systems, highlighting its potential for real-world applications. The results show that the WDDRE model can effectively manage the trade-offs between investment costs and operational resilience, providing a robust framework for enhancing the reliability and safety of power distribution networks against wildfires.

## V. Conclusion

In the context of wildfires ignited by component faults within distribution systems, planning decisions play a crucial role in influencing the robustness of the system. A crucial yet usually overlooked aspect of these decisions is their influence on the realization of potential wildfire disruption scenarios. To address this gap, the paper developed a novel two-stage wildfire-preventive decision-dependent resilience enhancement (WDDRE) model for distribution systems against endogenous wildfires. We introduce an innovative modeling method that captures both the wildfire ignition and disruption DDUs. Our modeling approach explicitly incorporates the interdependencies between system components and wildfire risk, enabling a more risk-informed modeling of wildfire propagation and system disruption. To the best of our knowledge, this is the first scalable resilience planning method that jointly models both ignition- and spread-coupled DDUs for distribution systems, supporting more risk-informed decision-making.

The effectiveness and superiority of the proposed WDDRE model were demonstrated through its application to modified IEEE 33-bus and 123-bus test feeders, where it effectively reduced wildfire risk and ensured system resilience. The results reveal that incorporating both wildfire ignition DDU and wildfire disruption DDU related to endogenous wildfires leads to more resilient and robust planning decisions.

The proposed method offers a novel approach to addressing the challenges of modeling interdependent variables within optimization problems involving DDUs. It also provides utility operators and policymakers with a tractable and extensible tool to support investment decisions that improve power system resilience amid increasing wildfire threats.

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