

Distribution Grid Planning for Wildfire Resilience under Decision-Dependent Uncertainty

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ABSTRACT

The interaction between power systems and wildfires can be dangerous and costly. In fact, the operation of distribution grids is liable for the outbreak of wildfires when extreme weather conditions arise. Therefore, investment planning should consider the impact of operational actions on the wildfires-related uncertainty, which directly affects line-failure likelihood. Neglecting this can compromise the cost-benefit evaluation in planning system investments against wildfire risk. In this work, we propose a decision-dependent uncertainty (DDU) aware methodology that prescribes the optimal portfolio of investments for distribution systems while considering that high power-flow levels through line segments in high-threat areas can ignite wildfires. The methodology identifies the best combination of system upgrades to provide the necessary leeway to operate the distribution system under wildfire-prone conditions. Case study indicates that by modeling the DDU relationship between power-flow and line-failures, investments are more accurate and better prepare the grid infrastructure to deal with wildfire risk.

KEYWORDS. Power Systems Investment Planning. Wildfire Resilience. Distributionally Robust Optimization. Decision-Dependent Uncertainty. Multi-Level Combinatorial Optimization under Uncertainty.

PM – Mathematical Programming. EN&PG – OR in the Energy, Oil and Gas. OC – Combinatorial Optimization

RESUMO

A interação entre sistemas de energia e incêndios florestais pode ser perigosa e custosa. De fato, o funcionamento de redes de distribuição é responsável pela eclosão de incêndios florestais sob condições meteorológicas extremas. Portanto, o fundamental considerar no planejamento de investimentos o impacto das ações operacionais na incerteza relacionada com os incêndios florestais, que afeta diretamente a probabilidade de falha da linha de distribuição. Negligenciar isto pode comprometer a avaliação do custo-benefício no planejamento de novos investimentos em sistemas contra o risco de incêndios florestais. Neste trabalho, propomos uma metodologia baseada em incerteza dependente de decisão (DDU) que prescreve o portfólio ideal de investimentos para sistemas de distribuição, considerando ao mesmo tempo que altos níveis de fluxo de energia através de segmentos de linha em áreas de alta ameaça podem desencadear incêndios florestais. A metodologia identifica a melhor combinação de investimentos no sistema para fornecer a margem de manobra necessária para operar o sistema de distribuição em condições propensas a incêndios florestais. O estudo de caso indica que, ao modelar a relação DDU entre o fluxo de energia e as falhas nas linhas, os investimentos são mais precisos e preparam melhor a infraestrutura da rede para lidar com o risco de incêndios florestais.

PALAVRAS CHAVE. Sistemas de Distribuição. Configuração da Topologia de Rede. Resiliência a Incêndios Florestais. Otimização sob Incerteza. Incerteza Endógena.

PM – Programação Matemática. EN&PG – PO na Área de Energia, Petróleo e Gás. OC – Otimização Combinatória.

1. Introduction

The potential for wildfires has increased worldwide, and the impact of human activities on wild lands combined with extreme weather conditions constitute one of the major causes for this issue [Jahn et al., 2022]. In the context of power systems, their interaction with wildfires can be particularly harmful given the wide presence of electrical networks and the high dependency on electricity in modern society. Apart from damaging different structures, wildfires can directly affect the operation of power systems. For instance, the sudden growth of temperature near the lines can reduce power lines' capacity temporarily, and the combination of heat and smoke can change the properties of the air gap, increasing the probability of short circuits [Serrano et al., 2022]. On the other hand, whilst wildfires have the potential to impact power systems, the operation of these systems, combined with certain environmental conditions, can also start wildfires. Within this context, it is critical to plan strategic investments that can increase the flexibility of power grids to avoid igniting wildfires while properly considering the role of electrical networks in initiating these events. Wildfires induced by power systems can be started mainly in two manners: when external objects (e.g., tree parts) come into contact with the power line or when the line itself comes into contact with nearby vegetation, equipment, or other lines [Wang and Bocchini, 2023]. In either case, the sequence of two events is necessary: a line fault followed by the ignition of nearby vegetation [Muhs et al., 2020]. The ignition process occurs when the power flowing in the conductor finds an alternative path to the ground, closing a circuit. This action can directly start a fire when close to vegetation by creating an arc or indirectly through molten metal particles, burning embers, or burning fluids. In this context, the higher the power flow, the higher the thermal stress of the lines, and the higher the chance of electric arcs to occur [Muhs et al., 2020].

Although power grid-induced ignitions are not the leading cause of wildfires, they are particularly threatening as they often occur in tandem with severe weather conditions (e.g., high wind and/or temperature and low humidity). As extreme weather can comprise vast areas, it can lead to multiple line faults and multiple ignitions. In addition, certain weather conditions can create a mechanism of rapid-fire growth and ember showers, which might result in multiple large fires and consequent catastrophic losses [Mitchell, 2013]. Some examples of wildfires initiated by power lines are (i) the "Black Saturday", which destroyed more than 400,000 ha and caused 173 human deaths in Victoria, Australia in 2009 [Teague et al., 2010]; (ii) the "Bastrop fire", that resulted in the death of 2 people and the loss of hundreds of homes, in Texas, USA in 2011 [Ridenour et al., 2011]; (iii) the "Camp Fire", which led to the death of 85 people in 2018, the deadliest wildfire in the history of California, USA [Maranghides et al., 2021]; (iv) the "Dixie fire", which burned an area larger than 300,000 ha in California, USA in 2021 [CAL FIRE, 2022]. Indeed, in California, out of the 20 most destructive wildfires observed in the past decades, at least 9 were caused by the interaction between electrical infrastructure and environment.

In this work, we propose a novel methodology to devise expansion and investment plans for distribution systems while considering the double role of power lines as assets that can affect and be affected by the uncertainty realization related to wildfires. The proposed approach links investments and operational decisions with the very initiation of the extreme event as we consider that power lines in high-threat areas can ignite wildfires. Within this context, we consider the installation of new lines and the hardening of existing ones, as well as the strategic allocation of switches in the distribution grid, as candidate investments to be chosen by the system planner to increase the operational leeway under wildfire-prone conditions. Structurally, the methodology falls into the class of a two-stage, three-level, Distributionally Robust Optimization (DRO) problem with Decision-Dependent Uncertainty (DDU). Roughly speaking, the DDU framework models the endogenous nature of uncertainty realizations when the uncertainty dynamics are influenced by the solution assigned to all or to part of the decision variables of the problem [Luo and Mehrotra, 2020]. Furthermore, we leverage the DRO framework as it is non-trivial to infer precise line failure probabilities. Structurally, in the first stage, the model determines the investment plan and the network topology configuration. In the second stage, the post-contingency multi-period operation is addressed, where the probabilities are adjusted according to the first-stage information and the investments made.

To summarize, the contributions of this work are:

1. To design a distribution grid expansion planning methodology that accounts for the double-sided role of operational decisions in wildfire-prone seasons. More specifically, we formulate a DDU-aware two-stage

DRO model that takes into account the impact of investments and power-flow levels on the wildfire uncertainty realization and the induced ambiguity state in the line failure probabilistic description to optimize investments aiming at providing distribution operators the necessary leeway to manage the system under wildfire-prone conditions.

2. To propose a framework that explicitly maps the relationship between first-stage operational decisions and second-stage wildfire uncertainty impact to properly balance the cost/benefit trade-off when devising investment plans for distribution grids. For this purpose, we improve the standard adjustable DRO problem class to account for an ambiguity set of line-failure distributions that depends on investments and operational points. Structurally, the resulting mathematical formulation has a three-level system of nested optimization models.
3. To construct a tailored iterative solution method capable of solving the proposed non-convex optimization problem in a finite number of steps. More specifically, we devise a set of reformulation procedures leveraging duality theory to develop an outer-approximation-based decomposition algorithm composed of tractable master- and sub-problems. Numerical experiments conducted in this work indicate that the proposed solution method can handle reasonable-sized instances in a practical computational time.

Summary of the Academic Products linked to this M.Sc. Dissertation

- **Published Journal Paper – Scopus Q1/96th:** Distribution System Operation Amidst Wildfire-Prone Climate Conditions Under Decision-Dependent Line Availability Uncertainty – *IEEE Transactions on Power Systems*. DOI: 10.1109/TPWRS.2024.3353593
- **Submitted Journal Paper – Scopus Q1/96th:** Decision-Dependent Uncertainty-Aware Distribution System Planning Under Wildfire Risk – *under review: IEEE Transactions on Power Systems*.

2. Problem Definition and Formulation

The main objective of the methodology proposed in this work is to determine the optimal portfolio of investments for distribution grids while explicitly considering the impact of power-flow levels on the potential ignition of wildfires. Methodologically, as illustrated in Figure 1, we formulate this investment planning problem as a two-stage distributionally robust optimization model that accounts for decision-dependent uncertainty. The first stage defines investments and topology configuration to minimize overall system expenditures, including the worst-case expected second-stage costs under a decision-dependent ambiguity set. The second stage accounts for a multi-period operation of the system. For expository purposes, the proposed first-stage optimization model is presented as the following concise representation:

$$\text{Minimize}_{\mathbf{x}_r, \mathbf{z}_r, \mathbf{y}} \quad \mathbf{c}^{inv\top} \mathbf{y} + \sum_{r \in \mathcal{R}} w_r \left(\mathbf{c}^{sw\top} \mathbf{z}_r + \mathbf{c}^{imb\top} \mathbf{x}_r + \sup_{Q \in \mathcal{P}_r(\mathbf{f}_r^p, \mathbf{y}^{ha})} \mathbb{E}_Q [H_r(\mathbf{z}_r, \mathbf{a}_r)] \right) \quad (1)$$

subject to:

$$\mathbf{A}\mathbf{x}_r = \mathbf{b}_r; \quad \forall r \in \mathcal{R} \quad (2)$$

$$\mathbf{C}\mathbf{x}_r + \mathbf{L}\mathbf{z}_r \geq \mathbf{m}_r; \quad \forall r \in \mathcal{R} \quad (3)$$

$$\mathbf{N}\mathbf{z}_r + \mathbf{P}\mathbf{y} \geq \mathbf{u}_r; \quad \forall r \in \mathcal{R} \quad (4)$$

$$\mathbf{y}, \mathbf{z}_r \in \{0, 1\}^{|\mathcal{L}|}; \quad \forall r \in \mathcal{R}, \quad (5)$$

with $\mathbf{x}_r$ and $\mathbf{z}_r$ denoting respectively the variables for operative decisions (comprising power-flow levels in the distribution lines $\mathbf{f}_r^p$), and topology configuration of each representative day $r \in \mathcal{R}$, and $\mathbf{y}$ accounts for the investment decision variables, including line hardening decisions ($\mathbf{y}^{ha}$). In the objective function (1), the first three terms stand for investments, switching, and imbalance costs, respectively. The last term represents the second-level problem (Subsection 2.1) that maximizes the expected value of the post-contingency operation. Function $H_r(\mathbf{z}_r, \mathbf{a}_r)$ denotes a third-level problem that minimizes the post-contingency operation for a given topology configuration ($\mathbf{z}_r$) and line availability scenario ($\mathbf{a}_r$). The set of constraints (2) represents the operative constraints that model active and reactive power balance. Furthermore, the block of constraints (3) represent voltage

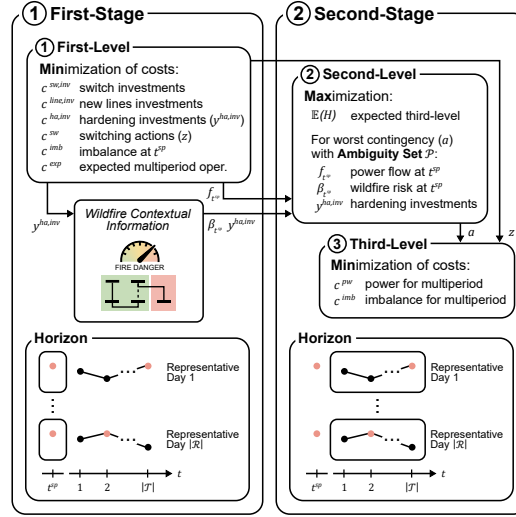


Figure 1: Proposed two-stage investment planning methodology as a three-level system of nested optimization models.

differences, active and reactive power flow interaction, and operative variables limits. The set of constraints (4) models the behavior of binary variables for topology and investment decisions, and constraints (5) define the binary nature of variables y and z_r , with $\mathcal{L}$ denoting the set of distribution lines.

The critical task of planning/operating agents is to balance supply and demand while respecting the system's constraints by exploiting all available and scheduled resources. In the context of this work, to appropriately define the investments to be made in the grid, this operational stage is represented as the third-level optimization problem under function H_r for each representative day $r \in \mathcal{R}$. Formally, the model is similar to the first-stage problem (1)–(5), except that a multi-period operation is considered, and the topology information (z_r) and line availability (a_r) are known. The compact formulation for a given $r \in \mathcal{R}$ of this third-level problem is presented in (6)–(8):

$$H_r(z_r, a_r) = \underset{x_{t,r}^c}{\text{Minimize}} \quad \frac{1}{|\mathcal{T}|} \sum_{t \in \mathcal{T}} \left(c^{oper \top} x_{t,r}^c \right) \quad (6)$$

subject to:

$$Ax_{t,r}^c = b_{t,r}; \quad \forall t \in \mathcal{T} \quad (7)$$

$$Cx_{t,r}^c \geq m_{t,r} - Lz_r + Va_r + W(z_r \odot a_r); \quad \forall t \in \mathcal{T}, \quad (8)$$

where the set of variables $x_{t,r}^c$ represents the variables for operative decisions of each period $t \in \mathcal{T}$ of a given representative day $r \in \mathcal{R}$. The operative decisions have the same role as the first-stage continuous decision variables in (1)–(5). Furthermore, as the operational stage (6)–(8) is aware of the contingency status of the line segments (i.e., a_r is an input), the model represents grid operation in a post-contingency state. Therefore, superscript c is used to highlight that the variables in this stage are being optimized considering contingencies, thus differentiating them from the first-stage variables. In this problem, the objective function (6) minimizes the hourly average cost associated with electricity purchase and active and reactive power imbalance at every bus. Analogously to the first-stage constraints, (7) represents operative restrictions (2) for each period $t \in \mathcal{T}$; and the set of constraints (8) represents operative constraints (3) for each period $t \in \mathcal{T}$. In this case, line availability will depend on the contingency variable a_r and on the first-stage topology configuration z_r . Operator $\odot$ stands for a Hadamard product, i.e., a component-wise multiplication between two vectors (a_r and z_r).

2.1. Decision-Dependent Ambiguity Set Modeling

Following the discussion in the previous sections, the proposed investment planning methodology (1)–(5) considers the impact of operational decisions on the line availability probabilistic characterization with the following term in the objective function:

$$\sup_{Q \in \mathcal{P}_r(f_r^p, y^{ha})} \mathbb{E}_Q \left[H_r(z_r, a_r) \right]. \quad (9)$$

Problem (9) stands for the worst expected cost of the multi-period post-contingency operation for a given representative day $r \in \mathcal{R}$ over the (ambiguity) set $\mathcal{P}_r(\mathbf{f}_r^p, \mathbf{y}^{ha}) \in \mathcal{M}_+$, whose components are essentially different line availability probability distributions given the limited knowledge of failure probabilities, which are also dependent on the power-flow and on the hardening investment (first-stage) variables $(\mathbf{f}_r^p, \mathbf{y}^{ha})$. In the proposed methodology, the definition of an investment plan considers the usual nominal failure probability level associated with each line segment but also incorporates the fact that environmental conditions can create wildfire-prone circumstances. In this latter context, we argue that the power-flow levels $(\mathbf{f}_r^p)$ impact the uncertainty characterization of the line availability. More specifically, the probability of a line starting a fire and becoming unavailable rises as the power through this line segment increases. Furthermore, as a counter-reaction, the hardening decisions $(\mathbf{y}^{ha})$ reduce line unavailability likelihood under extreme weather circumstances. Mathematically, the decision-dependent ambiguity set proposed in this work can be expressed as in (10):

$$\mathcal{P}_r(\mathbf{f}_r^p, \mathbf{y}^{ha}) = \left\{ \mathcal{Q} \in \mathcal{M}_+(\mathcal{A}_r) \mid \mathbb{E}_{\mathcal{Q}}[\mathbf{S}\hat{\mathbf{a}}_r] \leq \bar{\boldsymbol{\mu}}_r(\mathbf{f}_r^p, \mathbf{y}^{ha}) \right\}, \quad (10)$$

where $\mathbf{S}$ is a matrix defined as $[\mathbb{I} \mid -\mathbb{I}]_{2|\mathcal{L}| \times |\mathcal{L}|}$, with $\mathbb{I}$ being an identity matrix of size $|\mathcal{L}|$. The elements of vector $\hat{\mathbf{a}}_r = \mathbb{1} - \mathbf{a}_r$ are random variables associated with line unavailability, with $\mathbb{1}$ being a vector of ones and $\mathbf{a}_r$ indicating the availability of the line segments. Following standard industry and academic practices, the support of the random vector $\mathbf{a}_r$, is defined as:

$$\mathcal{A}_r = \left\{ \mathbf{a}_r \in \{0, 1\}^{|\mathcal{L}|} \mid \sum_{l \in \mathcal{L}} a_{l,r} \geq |\mathcal{L}| - K \right\}; \quad \forall r \in \mathcal{R}, \quad (11)$$

Essentially, (11) considers all failure events that involve at most K line segments. Moreover, in the framework proposed in this work, the decision-dependent vector-function $\bar{\boldsymbol{\mu}}_r(\mathbf{f}_r^p, \mathbf{y}^{ha})$ is defined as:

$$\bar{\boldsymbol{\mu}}_r(\mathbf{f}_r^p, \mathbf{y}^{ha}) = \boldsymbol{\gamma} + \text{diag}(\boldsymbol{\beta}_r \odot \mathbf{w}^\beta(\mathbf{y}^{ha})) \mid \mathbf{f}_r^p; \quad \forall r \in \mathcal{R}, \quad (12)$$

where vector $\boldsymbol{\gamma} = [\boldsymbol{\gamma}_l^\top \mid \mathbf{0}^\top]_{2|\mathcal{L}| \times 1}^\top$ comprises an estimated nominal probability of failure associated with each line segment $l \in \mathcal{L}$ and $\mathbf{0}$ is a vector of zeros of size $|\mathcal{L}|$. This vector $\boldsymbol{\gamma}$ characterizes the exogenous nature of failure. Each component of $\boldsymbol{\beta}_r$ stands for the endogenous relationship between failure probability and power-flow levels through a specific line segment. Essentially, as the absolute value of the power flow through a line segment $l \in \mathcal{L}$ raises, the corresponding failure likelihood increases by a factor of $\beta_{l,r}$. In this context, hardening decisions taken in the planning stage decreases the impact of power-flow levels on failure probabilities. Formally, the effect of hardening decisions is expressed by the element-wise multiplication between $\boldsymbol{\beta}_r$ and $\mathbf{w}^\beta$ in (12).

3. Solution Methodology

The two-stage formulation (1)–(5) is intended to optimally determine grid investments combined with topology configuration to improve the flexibility of the system to deal with wildfire-prone conditions. In the previous section, we formulate this decision-making process as a tri-level optimization problem that cannot be directly solved via off-the-shelf solvers due to its complex nature. Hence, in this work, we also provide a tailored solution methodology to address this problem. To design this methodology, we leverage the convex properties of the innermost models to write an outer-approximation-based decomposition algorithm composed of tractable master- and sub-problems. Following the definition of the ambiguity set in (10)–(12), for each representative day $r \in \mathcal{R}$, problem (9) can be expressed as the following mathematical programming formulation:

$$\sup_{\mathcal{Q} \in \mathcal{P}_r(\mathbf{f}_r^p, \mathbf{y}^{ha})} \mathbb{E}_{\mathcal{Q}}[H_r(\mathbf{z}_r, \mathbf{a}_r)] = \underset{\mathcal{Q} \in \mathcal{M}_+}{\text{Maximize}} \sum_{\mathbf{a}_r \in \mathcal{A}_r} H_r(\mathbf{z}_r, \mathbf{a}_r) \mathcal{Q}(\mathbf{a}_r) \quad (13)$$

subject to:

$$\sum_{\mathbf{a}_r \in \mathcal{A}_r} (\mathbf{S}\hat{\mathbf{a}}_r) \mathcal{Q}(\mathbf{a}_r) \leq \bar{\boldsymbol{\mu}}_r(\mathbf{f}_r^p, \mathbf{y}^{ha}) \quad : (\boldsymbol{\psi}_r) \quad (14)$$

$$\sum_{\mathbf{a}_r \in \mathcal{A}_r} \mathcal{Q}(\mathbf{a}_r) = 1 \quad : (\varphi_r), \quad (15)$$

which essentially identifies a probability measure $\mathcal{Q} \in \mathcal{M}^+$ that maximizes the expected cost of the post-contingency operation (6)–(8) while respecting (14) and (15). Due to its convex properties, model (13)–(15) can be equivalently rewritten in its dual version as:

$$\text{Minimize}_{\psi_r, \varphi_r \in \mathbb{R}} \left\{ \psi_r^\top \bar{\mu}_r(\mathbf{f}_r^p, \mathbf{y}^{ha}) + \varphi_r \mid \begin{array}{l} \psi_r^\top S \hat{\mathbf{a}}_r + \varphi_r \geq H_r(\mathbf{z}_r, \mathbf{a}_r); \quad \forall \mathbf{a}_r \in \mathcal{A}_r \\ \psi_r \geq \mathbf{0}; \end{array} \right\}$$

where variables ψ and φ are the dual variables associated with constraints (14) and (15), respectively. Within this framework, problem (1)–(5) can be equivalently written as:

$$\text{Minimize}_{\substack{\mathbf{x}_r, \mathbf{z}_r, \mathbf{y}, \\ \psi_r, \varphi_r}} \quad \mathbf{c}^{inv^\top} \mathbf{y} + \sum_{r \in \mathcal{R}} w_r \left(\mathbf{c}^{sw^\top} \mathbf{z}_r + \mathbf{c}^{imb^\top} \mathbf{x}_r + \psi_r^\top \bar{\mu}_r(\mathbf{f}_r^p, \mathbf{y}^{ha}) + \varphi_r \right) \quad (16)$$

subject to:

$$\text{Constraints (2)–(5)} \quad (17)$$

$$\psi_r^\top S \hat{\mathbf{a}}_r + \varphi_r \geq H_r(\mathbf{z}_r, \mathbf{a}_r); \quad \forall \mathbf{a}_r \in \mathcal{A}_r, r \in \mathcal{R} \quad (18)$$

$$\psi_r \geq \mathbf{0}; \quad \forall r \in \mathcal{R} \quad (19)$$

$$\varphi_r \in \mathbb{R}; \quad \forall r \in \mathcal{R}, \quad (20)$$

Furthermore, constraints (18) can be expressed equivalently as:

$$\varphi_r \geq \max_{\mathbf{a}_r \in \mathcal{A}_r} \left\{ H_r(\mathbf{z}_r, \mathbf{a}_r) - \psi_r^\top S \hat{\mathbf{a}}_r \right\}; \quad \forall r \in \mathcal{R}, \quad (21)$$

with the right-hand-side of (21) a bi-level (max-min) optimization problem. The decomposition procedure is then built over (16)–(20), acknowledging the equivalence between (18) and (21). Firstly, recall that $H_r(\mathbf{z}_r, \mathbf{a}_r)$ is a convex minimization problem. Thus, we can equivalently re-write the right-hand-side of (21) as a single-level Mixed-Integer Linear Programming (MILP) model by replacing the optimization problem $H_r(\mathbf{z}_r, \mathbf{a}_r)$ by its dual formulation. This resulting MILP problem is referred to as the *sub-problems* (one for each $r \in \mathcal{R}$) and can be handled efficiently by MILP algorithms or off-the-shelf solvers. The *master-problem* is then a relaxation of (16)–(20) by accounting for only a subset $\hat{\mathcal{A}}_r \subset \mathcal{A}_r$, $\forall r \in \mathcal{R}$. The proposed iterative procedure works as follows: (i) for a given $\mathbf{z}_r$ and ψ_r , solve the *sub-problems* and store the optimal value of $\mathbf{a}_r$ and the respective dual variables of $H_r(\mathbf{z}_r, \mathbf{a}_r)$; then (ii) replace $H_r(\mathbf{z}_r, \mathbf{a}_r)$ in (18) by the objective function of the dual problem of $H_r(\mathbf{z}_r, \mathbf{a}_r)$ fixed the optimal dual solution; this characterizes an outer approximation for $H_r(\mathbf{z}_r, \mathbf{a}_r)$, or a valid cutting plane; then add the optimal $\mathbf{a}_r$ found into $\hat{\mathcal{A}}_r$; and solve the master-problem with this new block of cutting planes identifying a new $\mathbf{z}_r$ and ψ_r . To check for convergence, note that the master problem is a lower bound of (16)–(20), and the sub-problems compose an upper bound. Therefore, by comparing these upper- and lower-bounds, we can assess the accuracy of the outer approximation up to an ε -convergence.

4. Case Study

To illustrate the applicability of the proposed planning methodology, we use a 54-bus system with 57 lines based on Moreira et al. [2024]. We consider a 24-hour operation of 4 days representing a 1-year evaluation. The first two days represent operations during winter and spring, respectively, when we assume the wildfire risk is negligible. The third day corresponds to summer/fall, also without wildfire risk, and the fourth day is associated with a summer/fall period when there is a high probability of wildfire occurrence. A simplified diagram of the test system is shown in Figure 2 for each of the 4 representative days under consideration. The complete diagram can be accessed in Piancó et al. [2024]. Furthermore, we assume $K = 1$ in (11) to characterize the support set $\mathcal{A}$.

4.1. Main Results

To better analyze the proposed planning methodology, we first evaluate the model without the decision-dependent aspect, i.e., parameter β set to zero in (12) (we, hereinafter refer to this case as “without DDU”). Then, we run the model considering the configuration for the wildfire risk (the “with DDU” case). We compare both results from the planning and switching decisions perspective. As shown in Moreira et al. [2024], the “with DDU” case can leverage the cutting planes of the “without DDU” case as a warm-up phase. The key results of this

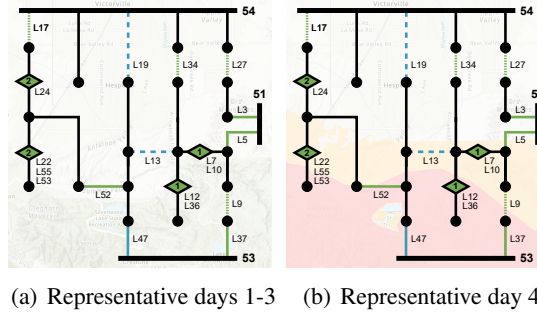


Figure 2: Simplified network representation of the 54-bus system with substations, selected buses, and lines characterized, respectively, by black rectangles, black circles, and line segments. Lines candidates for investment are presented as blue dashed lines. Hardening investments are indicated by green diamonds.

comparison are presented in Table 1. The “with DDU” case has as a solution a portfolio of different investments, prescribing the construction of lines 17 and 34, and turning lines 5 and 52 to be switchable. Hardening investments were made only in the “with DDU” case, where lines 22 and 55 with the hardening investment option 2 (line coating). These investments allow for topology reconfiguration for representative day 4 when there is wildfire risk. It can be noted that if no switching actions are performed, the buses inside the wildfire-prone area are entirely supplied by substations 51 and 53. When the topology reconfiguration is performed, these buses have their energy mostly supplied by bus 54. In this configuration, these buses become the end of their branches, with a reduced power flow through the lines inside this high-threat area and, consequently, a decrease in the wildfire risk. We also analyze both cases from a financial viewpoint. The solution for the “with DDU” case would require an investment of \$ 1,230, \$ 3,753, \$ 86,066, respectively, for switching devices, line construction, and line hardening investment, summing up \$ 91,049 per year. On the other hand, the “without DDU” case has no investment or switching action prescribed, as there is no incentive to change the topology.

Table 1: Main results. ^a The running time for the “with DDU” case is 38.3 min. As we considered the “without DDU” cutting planes that lasted 27.5 min, it resulted in a total running time of 65.8 min.

		W/out DDU	With DDU
New lines		-	17; 34
New switchable lines		-	5; 52
Sw. actions (line index)	Day 1, 2, and 3	-	-
	Day 4	-	5; 17; 19; 34; 47; 52
Hardening investments	1	-	-
	2	-	22; 55
Annual Investment Costs (\$)		0	91,049
Solution Time (min)		27.5	65.8 ^a

4.2. Out-of-sample Analysis

With the planning and switching decisions (grid topology and investments) defined for both “with DDU” and “without DDU” cases, we perform an out-of-sample analysis using Monte Carlo simulation. In the simulation, a one-year operation is considered as one scenario, and we simulate 500 scenarios. By doing this analysis, we can verify the value and impact of considering the DDU aspect for the distribution system planning and operation. First, we calculate the total active power deficit proportion compared to the entire demand of the whole year. Then, we calculate two reliability metrics, SAIDI (System Average Interruption Duration Index) and SAIFI (System Average Interruption Frequency Index). The results of all scenarios show an average loss of active load of 5.5% of the total demand in a year for the “without DDU” case and a value of 0.4% for the “with DDU” case. This difference can also be perceived when we evaluate the loss of load in terms of $CVaR_{95\%}$. While the “without DDU” case has a $CVaR_{95\%}$ of 5.6%, the “with DDU” case has a $CVaR_{95\%}$ of 0.4%. The loss of load observed

in both cases can be summarized in monetary values. On average, the cost of the deficit for a year would be \$ 5,804,245 and \$ 384,486 when considering the “without DDU” and “with DDU” cases, respectively. Furthermore, as previously discussed, the operation of the “with DDU” case would require an annual investment of \$ 91,049, and the “without DDU” case would not require any investment. This cost of investment pays out since the difference in the average expected cost of loss of load between cases is \$ 5,419,759. Finally, regarding the reliability metrics, the customers of this grid would expect, on average, 280 hours with no energy or 11.7 days in a year (SAIDI) if the grid was planned following the “without DDU” case. In this context, these customers would expect, on average, 59 interruptions throughout the year (SAIFI). On the other hand, if the grid were planned following the decisions indicated by the “with DDU” case, customers would expect, on average, 18 hours (SAIDI) with no energy and 14 interruptions (SAIFI) throughout the year. In addition, while the “without DDU” case has a $CVaR_{95\%}$ of SAIDI equal to 284 hours and a $CVaR_{95\%}$ of SAIFI equal to 62 interruptions, the “with DDU” case has a $CVaR_{95\%}$ of SAIDI equal to 19 hours and a $CVaR_{95\%}$ of SAIFI equal to 16 interruptions. For comparison purposes, we also evaluated the model with a counterfactual of 500 scenarios assuming no wildfire risk for the representative day 4. On average, the results for the deficit, SAIDI, and SAIFI are, respectively, 0.02 % of total demand, 1.2 hours, and 0.5 interruptions.

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